Master's Thesis

A Three-dimensional Deviation Analysis by the Coordinate Registration of Randomly Positioned Objects

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2018

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A thesis
submitted to the Graduate School of UNIST
in partial fulfillment of the
requirements for the degree of
Master of Science

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12. 19. 2017
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Abstract

It is very important to accurately inspect machining errors, assembly tolerances of product in manufacturing industry. Recently, a three-dimensional measurement system is widely used for industrial inspection. Typical three-dimensional measurement methods include a coordinate measuring machine (CMM), a line laser scanning method, and a structured light system comprising a camera and light source for generating a pattern. In general, the inspection system applying the three-dimensional measurement method require the physical calibration processing using special device to place object at home position with desired pose. However, such a process requires a considerable time for measurement, and it inhibits the flexibility of measurement spatially.

Therefore, to solve this problem, this thesis proposed a methodology to measurement of randomly positioned objects by coordinate recognition. It is assumed that the position and pose of object is varied at every measurement. Coordinate of CAD model must be brought to the coordinate of measured data to calculate deviation of object. Transformation parameters of two coordinates are derived by following procedure. reference plane selection is preceded before measurement as preprocessing. The first step is rough registration based on principal component analysis and iterative closest point algorithm. The second step is main methodology of this thesis, which is coordinate adjustment to calibrate transformation parameters. Coordinate adjustment is composed of two stages, which are reference plane matching for calibrating rotation parameters and edge matching for translation parameters. Then, deviation is calculated by comparison to the CAD model.

Table of Contents

List of Figures

I. Introduction

1.1 Background

Nowadays, demands on developing automatic measurement system is increasing in manufacturing industry since the quality of the product is essential to manufacturing industry (Herakovic, 2010). There are many purposes of measurement of the geometric dimension accuracy such as checking machining error and assembly tolerances of product.

Recently, as the shape of an object to be measured becomes complicated, a three-dimensional measurement device is used more than a two-dimensional vision camera. For example, automotive assembly is a very complex task because it consists of many parts. The geometry of each of these components must be measured to the correct dimensions to ensure reliable operation of car. Because of mechanical uncertainties, the geometrical dimension of manufactured product may be different from ideal CAD model. To evaluate these deviations automatically, manufactured parts should be digitalized. To do this, 3D measurement system is applied to generate point cloud that are compared to nominal CAD data on the object surface (Teutsch, 2007).

Laser scanners, structure light and contact scanner are the mainstream of industrial scanning technology. Coordinate measurement machine(CMM), which is one of contact approach, is the slowest, but the most precise. White light or laser scanners accurately digitize objects to capture fine detail and capture free-form surfaces without reference points or spray. The entire surface is covered at a record speed without risk of component damage. Graphical comparison charts show geometric variations across the entire object level and provide in-depth insight into potential causes

1.2 Motivation

Most of the inspection system applying 3D measurement device require hardware system such as a special moving device including fixtures to place the product at a desired home position. For example, contact device require the object to be stopped, carefully positioned, and then repositioned several times manually (Newman and Jain 1995). Such a process requires a considerable time for measurement, and it inhibits the flexibility of measurement spatially.

In general, vision system is used for inspection of a product with high precision at the end of line. However, this is not enough to manage the quality of the product. Therefore, it is important to inspect the product quickly in process. At this time, there is no enough time to align the position of the product or to adjust the origin. Therefore, it is necessary to develop a technique to recognize the coordinate of randomly positioned objects automatically. In-process product is randomly positioned while moving on the conveyor or when robot does not place the product at a predetermined location

Therefore, mathematical approach is necessary for automated inspection industry, which could eliminate the need for physical home positioning steps using specialized fixtures (Sabri *et al.*, 2016). Even if the position and pose of the measuring object are different from ideal one, it is needed a system capable of recognizing the coordinate and performing the inspection (Figure I-1 (a)). This would be possible if the algorithm that aligns the measurement coordinate and the CAD coordinate with adaptable precision to be used for the measurement.

In addition, the coordinate recognition algorithm has a field to be utilized besides the measurement system. It is a robot bin picking system. In bin picking system, the robot sequentially picks randomly place objects from container as shown in Figure I-1 (b). In the bin picking system, the use of 3D vision is expanding beyond the conventional 2D camera and 1D distance collection device. The reliable 3D coordinate recognition algorithm proposed in this paper can be used to find out the pose and position by scanning the parts with 3D vision and comparing it with the CAD model.

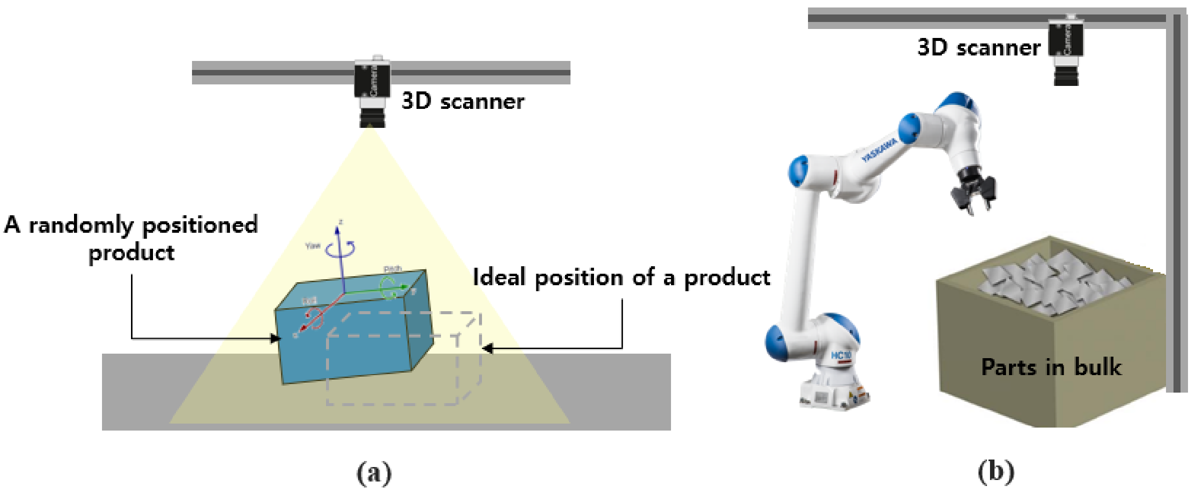


Figure I-1 (a) In-process 3D measurement of an object (b) Bin picking system

1.3 Objective

Therefore, to solve this problem, this thesis proposed a methodology to measurement of randomly positioned objects by coordinate recognition. It is assumed that the position and pose of object is varied at every measurement. Coordinate of CAD model must be brought to the coordinate of measured data to calculate deviation of object (Newman *et al.*, 1995).

The target application of this approach is inspection of assembly quality of in-process product and deformation analysis of car body finishing machining. The method should even deal with object is randomly positioned with variation on X, Y, and Z translation along the X, Y, and Z directions and rotation angle around the X, Y, and Z axes. Also, whole inspection process should be fully-automated and real-time in order to apply in-process inspection. Accuracy should be ensured since its application is measurement. Tolerance from this matching algorithm should be under twice measuring device error.

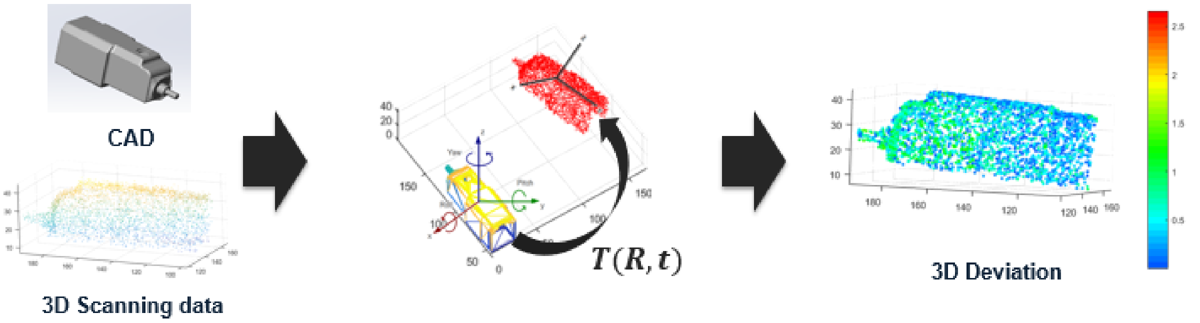


Figure I-2. 3D deviation analysis of a randomly positioned object

1.4 Outline of the thesis

This thesis consists of five chapters. Chapter 1 introduce the demand for mathematical approach of measurement of randomly positioned objects. In Chapter 2, literature survey is performed about 3D data acquisition system and 3D registration methods. The detail of proposed 3D registration algorithm for measurement of randomly positioned object is described on Chapter 3. Transformation parameters of two coordinates are derived by four steps. In Chapter 4, a case study about housing of electric tooth brush is described. Lastly, the conclusions and future research are described in Chapter 5.

II.Literature Survey

2.1 3D Point Data Acquisition

A 3D point data acquisition device is used to collect 3D coordinate of an objects. Difference technical principle are applied in measuring the objects needed to gather a 3D geometry. These data acquisition devices are mainly classified according to technical principles, which are contact and non-contact(Bi *et al.*, 2010).

2.1.1 Contact

Contact device touch the surface of object with a probe at the end of an arm, so called tactile method. It could measure the displacement caused by positioning a z pointer in the 3D space using calibrated sensor. Main advantage of this technique is high reliability and accuracy. However, slow performance and need of touching the objects are not feasible for dynamic application and time-consuming.

Coordinate measurement machine(CMM)

Measurement by CMM is defined by probe attached to the three moving X,Y and Z axes of the machine. These axes are orthogonal to each other and have a scale system that indicates the location of the axis. Probes could be mechanical, optical, laser or white light. The machine use the X,Y,Z coordinates of points to determine the size and position of objects. These points are collected by using a probe and the probe is positioned manually by and operator or automatically using control software.(Peggs *et al.*, 1999)

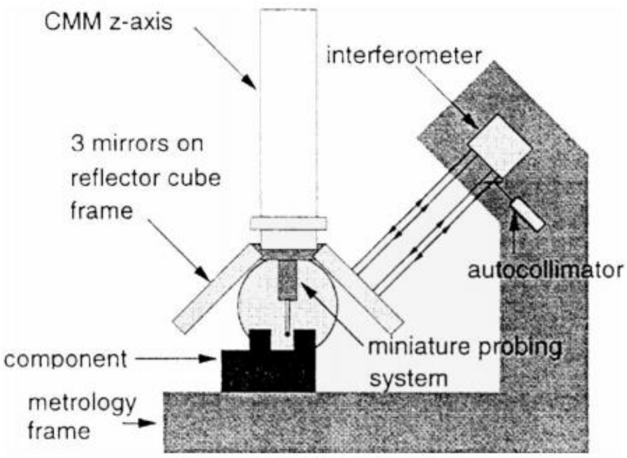


Figure II-1. Coordinate measurement machine (Peggs *et al.*, 1999)

2.1.2 Non-contact

Non-contact device interacts with objects using a media such as light and sound. Thus, it does not deform objects. This method uses cameras and process the images to reconstruct the 3D surface of object (Cui *et al.*, 2013). The reconstruction can be achieved by using camera or combining cameras and an active device. Non-contact technique also could be classified in terms of physical principle (Bi & Wang, 2010). Three principles frequently used in manufacturing are reviewed in this paper, which are triangulation, time of flight and structured light.

Triangulation

Triangulation is based on the principle of distance measurement by angle calculation.A laser stripe is projected on an objects and reflected beam is detected by camera, such as CCD. Through image processing and triangulation method, 3D coordinates of object are calculated (Figure II-2). Laser scanner have been widely used for inspection in industry by its high degree of accuracy.

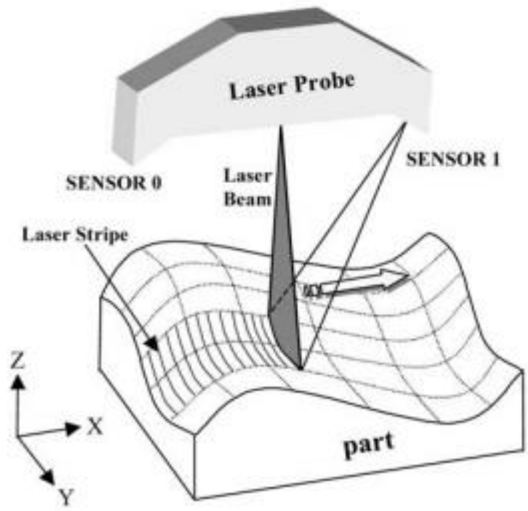


Figure II-2 Laser Scanning Mechanism (Son *et al.*, 2002)

However, laser scanners are usually manually operated (Son *et al.*, 2002). Therefore, Son et al suggest an automated measuring system process; the system consists of laser scanning device and software module. However, the system still requires a part setup process, which is alignment process of fixture using the dial indicator. In the system, the test part is positioned on the motorized rotary table. Each axis of the rotary table is aligned with the axis of the laser scanner using the dial indicator mounted on the laser scanner. Then, a specially designed fixture is attached and positioned on the table. Finally, the test part can be located inside the fixture

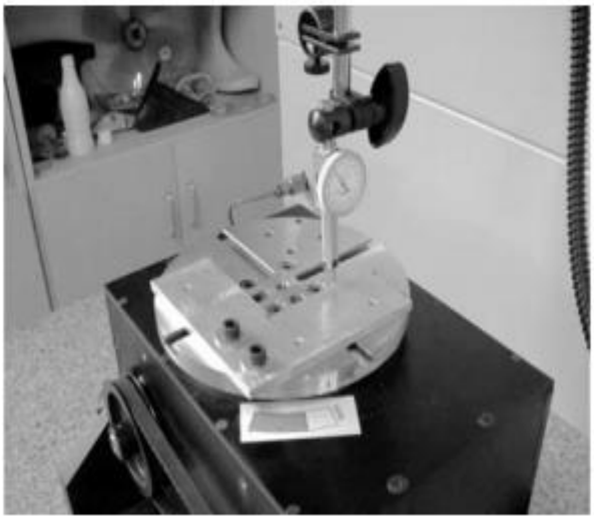


Figure II-3. Setup of a fixture and a rotary table (Son *et al.*, 2002)

Time of flight(ToF)

A laser emits a pulse of light and the surface of an objects reflects light back towards a receiver. The amount of time between transmission and reception is measured for the z distance of a surface. The round-trip time determines the travel distance of the light by using the speed of light. Therefore, the accuracy of ToF device depends on how precisely time is measured (Gokturk *et al.*, 2004). ToF camera returns 3D data directly. However, it does not produce high quality scans. It has some high noise level, low X,Y resolution and systematic measurement bias. Therefore, it is proper to object detection and part of natural user interface (Cui *et al.*, 2010). This device is suited to distance measurement at medium to long ranges. The device could only detect the distance of surface in its direction of view. Thus, the scanner should change the view direction to scan difference view. Typically, 3D ToF laser scanner can measure 10,000~100,000 point at once.

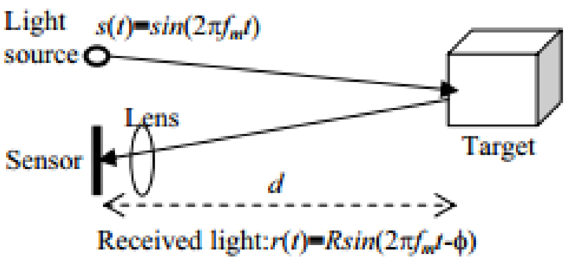


Figure II-4.Time of flight measurement (Gokturk *et al.*, 2004)

Structured light

Scanner project multiple stripe or pattern of light on the surface of object. Then camera look at the deformation of the pattern on the surface. A camera offset slightly from the projector and look at the pattern and calculate the distance of each point in field of view. Interferometry is useful for object having small detect on large flat surfaces and small depth variation. The accuracy for this device is quite high up to nanometer level recently. The main advantage of this method is speed and precision. Some high-tech device is possible to directly detecta very small defects without destroying the object, even detect stress on surface. The speed is also faster than other methods, so it can be very effective in manufacturing industry.

2.2 3D Measurements for Randomly Positioned Objects

Traditionally, objects should be placed at the home position with special fixtures or tools to totally dedicated to specific products (Y. Li *et al.*, 2006). The fixtures hold the objects in a desired position and orientation for accurate comparison between CAD model and measure data. This process needs time-consuming and costly effort is needed to design a new fixture.

In case of 3d measurement of randomly positioned object, the point cloud from scanning data and reference CAD model are in two different system. Scanning data exists in the measurement coordinate system(MCS), while CAD model exist in design coordinate system(DCS). To evaluate deviation of object, scanning data and CAD model must be brought to the same coordinate system through registration. Mathematically, registration means finding an optimal transformation matrix between the DCS and the MCS (Abenhaim *et al.*, 2011). Registration is also called localization or alignment of coordinates (Y. Li & Gu, 2006).

Generally, 3D data registration consists of two steps, which are a coarse registration and find registration. In a coarse registration, two datasets are aligned roughly using corresponding 3D features. The feature extraction and matching step can be approached different ways, which are target based matching and feature-based matching. After then, fine registration optimally aligns the roughly registered datasets. The general fine registration strategy is point based matching that process all individual points in datasets.

2.2.1 Target based matching

This method inserts reference things to objects, so called targets. Target should be recognizable in the difference scans. The targets must be visible in each scan at least three of them. In each scan, coordinate of center points calculated by each target. Then the targets identified in each scan are matched. The advantage of this method is it is reliable and accurate. However, it needs to carefully position the targets since at least three targets should be seen each scan to be co-registered.

Shi & Liang used Reference Point System(RPS) alignment method by using reference sphere located on part. Shi & Liang employed uncoded reference point in order to identify 3D coordinates of product and align point cloud sets to a common coordinate system such as reference CAD model (Shi *et al.*, 2016). The system is applied on a structured light range scanner system. For well-detected and aligned uncoded reference point selection, each point is assigned a unique identification in the software. Also, they used some criterion of applying uncoded reference points to a product surface such as sized of uncoded reference point, plane or curve which reference points are positioned or number of points.

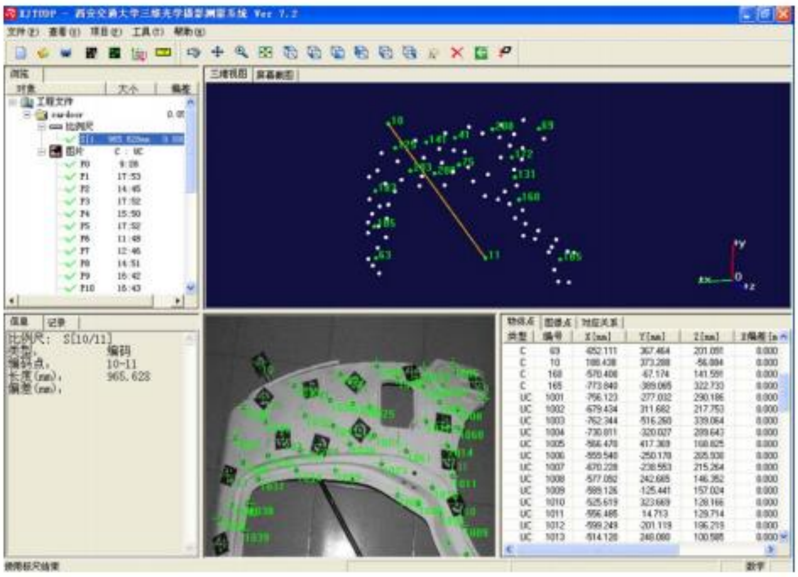


Figure II-5. 3D reconstruction of coded and uncoded reference points (Shi & Liang , 2016)

S. Gerbino et al. emphasize on alignment process of point cloud sets to the reference model for 3D laser scanning. Mainly, they pay attention to optical devices capturing the surface of product and providing information on the process variability and the deliverability of the quality of the product. (Gerbino *et al.*, 2016). In their method, Reference Point System(RPS) alignment method are used to align point cloud sets to reference model. Reference spheres of diameter 1mm or 0.5mm are located on parts.

2.2.2 Feature based matching

The feature based matching algorithm extract high-level feature from measured data before the actual matching steps. There are various kind of feature, usually including basic geometric shape such as lines, polygon or arcs (Laboureux *et al.*, 2001). The main advantage of this method is lower computational cost of the matching phase (Dutagaci *et al.*, 2012).

However, this method can only operate in feature-rich environment. Well-structured environment elements consisting of large flat surface and regular, geometric shapes are needed in this approach (Konecny *et al.*, 2016) .

Various kind of interesting point detection algorithms is used feature detection for registration. In addition, detection of interest point is used in several applications such as mesh simplification, mesh segmentation, viewpoint selection.(Bosché, 2012) These algorithms provide local feature that are invariant to rotation, scaling, noise, deformation, and articulation.

Mash saliency

Key feature of mesh saliency is local curvature over the surface (Lee *et al.*, 2005). The two scale Gaussian filters are applied to the mean curvature per each vertex. The scale is twice the other. The difference between two weighted curvature became the mesh saliency at that scale pair. (Castellani *et al.*, 2008)High mesh saliency indicates the corresponding vertex is salient for various scales. If total mesh saliency of a vertex is higher than all its neighboring vertices, the vertex is marked as candidate interesting point. If the candidate points with a saliency is higher than a threshold became final interesting points, which means local feature. Generally, the threshold is set to the average of the total mesh saliency over the local maxima.

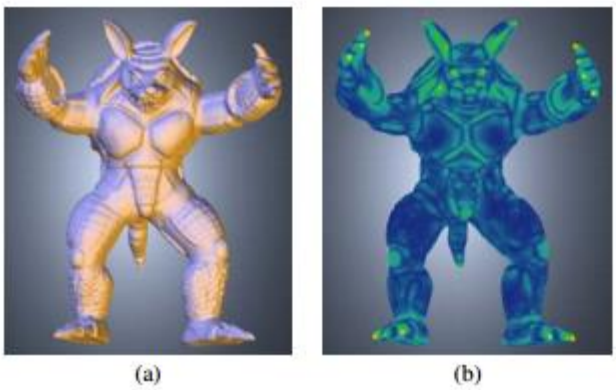


Figure II-6. Mesh Saliency (a) model (b) mesh saliency of model (Lee *et al.*, 2005)

Fast Point Feature Histogram(FPFH)

FPFH is based on a histogram of the difference of angles between the normal of the neighbor points (Rusu *et al.*, 2009) It is advanced version of Point Feature Histogram(PFH) retaining the discriminative power of the PFH. Point Feature Histogram is pose-invariant local features that represent the surface model property at a point. It is based on combination of geometrical relations with neighboring points. 3D point coordinate, which are x, y, z, and surface normal of that point, which are *nx, ny, nz*, are incorporated and then used as the other properties such as curvature. it attempts to capture as best as possible the sampled surface variations by taking into account all the interactions between the directions of the estimated normal. The difference between the two normal of two points can be expressed as a set of angular features. FPFH is simplified version by re-determining the PFH values by weighting. The weight represents a distance between the query point and a neighbor point.

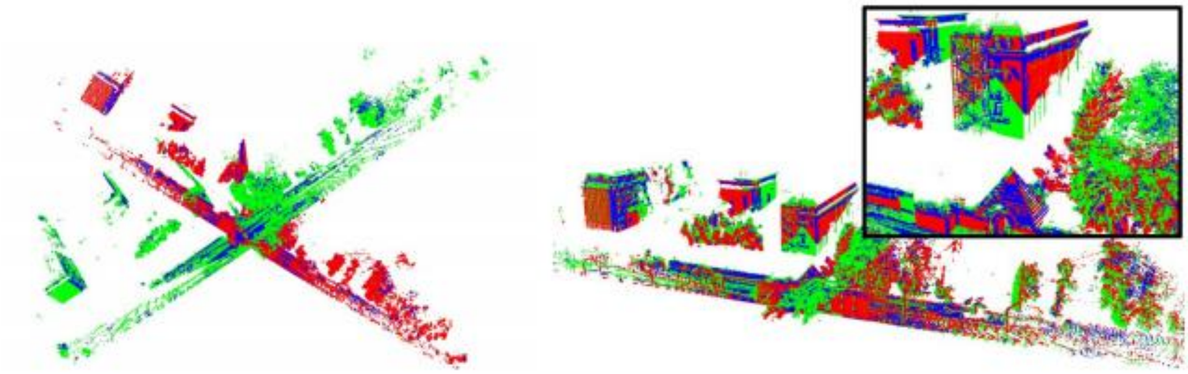


Figure II-7. Registration using FPFH feature points; feature point is blue(Rusu *et al.*, 2009)

2.2.3 Point based matching

Point based matching processes all individual points in measured data. It provides alignment result of two point cloud data with a high accuracy (Mark, 2010). Therefore, it is usually applied in fine registration steps. But its main disadvantage is its high computational costs by considering all individual points. It is applicable in complex and non-structured environment(Pomerleau *et al.*, 2013).

Iterative closest point(ICP)

Iterative Closest Point (ICP) algorithm represents an alignment tool which iteratively minimizes distances of corresponding points within two datasets. ICP use the pair of closet points in a pair of point cloud. A transformation parameter for both rotation and translation is calculated between two different data (Dai *et al.*, 2007).

The ICP algorithm can be summarized as five steps. First is removal for the remote point. Second, pair of closest points is assigned, one is from the reference scan; corresponding one is from the test scan. Next, the pairs with the long distance is rejected. Then, the loss function is calculated. If the loss function is minimized, iterative process is stopped (Estépar *et al.*, 2004).

To begin, the ICP algorithm needs initial guessing to iteratively modify it (Rusinkiewicz *et al.*, 2002). If the initial guess movement and rotation values are too far from the actual value, the ICP algorithm may fall to the local minimum. At a minimum, the ICP algorithm will stop iterations because of the cost associated with moving to the minimum. A new initial guess and an initial pose are calculated each time the ICP trail is run. If the view is well constrained, it will generally converge to the correct alignment. If the view is subject to poor constraints, the initial guess can drop the ICP algorithm to the local minimum (Zhang, 1994).

However, some limitation still exists regarding to robust registration and accuracy demands. For example, systematic errors impede the comparison with multisensory data (Krell *et al.*, 2017). Therefore, some post-processing research have been studied to improve the quality of data. In this problem, the Iterative Closest Point (ICP) algorithm represents an alignment tool which iteratively minimizes distances of corresponding points in two sets of data. Although ICP is widely used, it is often applied as a black-box application within 3D data post-processing for surface reconstruction.

III. 3D Deviation Analysis of Randomly Positioned Objects

3.1 Problem Statement

In general, 3D measurement system such as CMM places the target object on home position for accurate comparison between scanning data and reference CAD model. Precision of measurement result could be guaranteed by direct comparison with CAD model when the object is always positioned on desired position and orientation. Similar case can be found in our life. When using copy machine, user aligns paper to origin to copy as intended. However, these kinds of physical process are costly and time and effort.

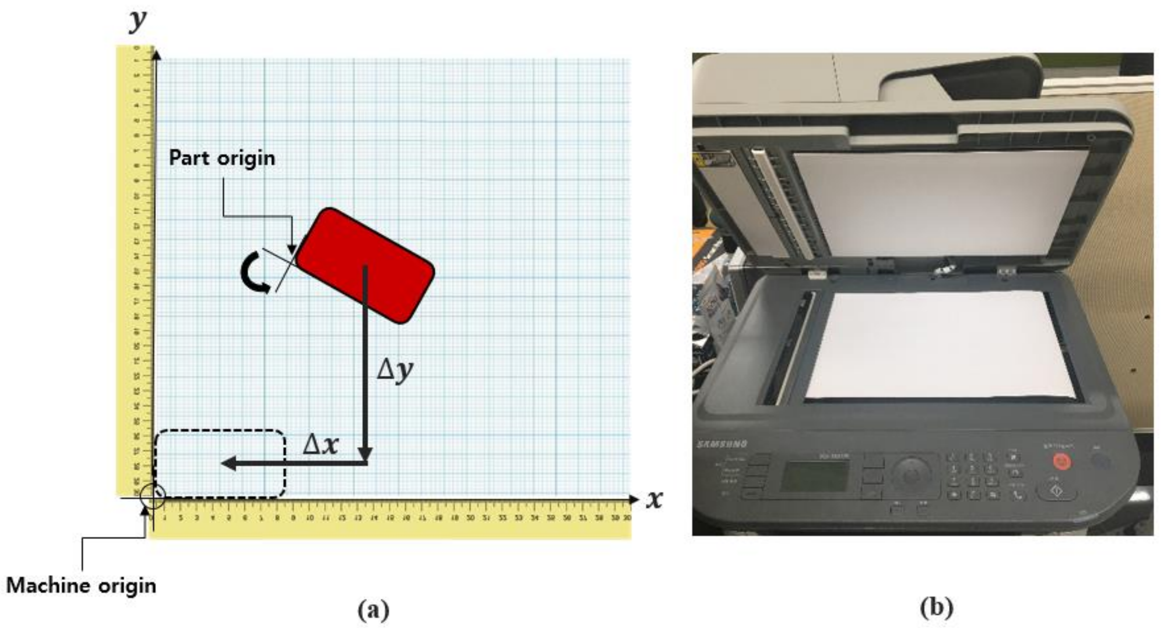


Figure III-1. (a) Home positioning (b) Example of home positioning (copy machine)

Otherwise, some software packages support point-based manual registration. Operator selects matching 3D points in scan data and CAD model. This manual method is also in-efficient in respect to both time and accuracy.

Therefore, mathematical approach is needed that could eliminate the need for physical home positioning steps. The proposed method is carried out by acquiring the scan data from non-contact measurement device such as laser scanning and then comparing it with CAD model for deviation analysis.

The target application of this approach is inspection of assembly quality of in-process product and deformation analysis of car body finishing machining. The method should even deal with object is randomly positioned with variation on X, Y, and Z translation along the X, Y, and Z directions and rotation angle around the X, Y, and Z axes. Also, whole inspection process should be fully-automated and real-time in order to apply in-process inspection.

Accuracy should be ensured since its application is measurement. Tolerance from this coordinate registration process should be under twice of measuring device error. In this thesis, measurement error from device is 1mm. Therefore, allowable tolerance is 2mm. By proposed coordinate registration process, defect over 2mm on the object will be detected.

A number of well-documented localization algorithms have been developed, and these kinds of algorithm could be applied to this problem. Localization, so called registration, is the process of transforming the scanning point cloud data from measurement coordinate systems(MCS) to design coordinate system(DCS) (Mehrad *et al.*, 2013). The usual way of registration algorithm is to perform a coarse registration, which approximately aligns the two datasets in the same coordinate, and then carry out a fine registration (Figure III-2) (Bellekens *et al.*, 2014). Most of research on registration use novel method of fine registration, Iterative Closest Points(ICP).

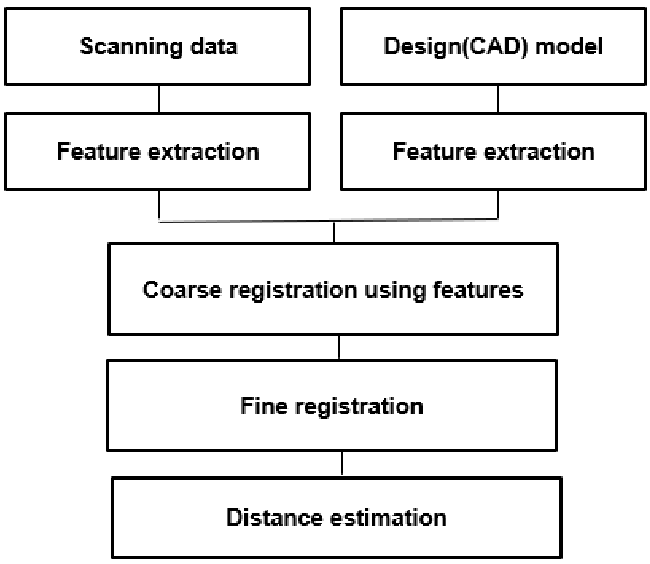


Figure III-2. Conventional registration process (Kim *et al.*, 2011) (Ji *et al.*, 2017)

Although ICP enables searching for a more optimal solution than the result achieved through coarse registration, but it often reaches a wrong convergence. Especially, an erroneous point correspondence between the two point cloud data can increase the distance between them under optimization, even if they are overlapping (Marani *et al.*, 2016).

In this paper, coordinate adjustment technique is introduced for optimal alignment after carrying out fine registration, which is ICP. Coordinate Adjustment consists of two steps which are reference plane matching and edge matching.

This system uses only point cloud captured at once by a 3D measurement device for real-time application. In general, registration algorithm is also used to merge point cloud datasets gathering from different viewpoints. However, scan-to-scan matching, which is point cloud registration from multi-camera, is not covered this paper. The purpose of this study is precise matching between scan data and CAD model for deviation analysis.

3.2 Registration and Adjustment Processes

3.2.1 Overview

A precise registration algorithm for 3D deviation analysis of randomly positioned object is proposed in this thesis. In inspection system, the measured point cloud data may have arbitrary 3D location an orientation in global coordinate system. In this approach, design coordinate system of CAD model is transformed to measurement coordinate system for comparison. Therefore, measurement coordinate system should be recognized for registration scanning data with CAD model. System input is scanning data and output is transformation matrix between scanning data and CAD model. Rigid transformation matrix consists of rotation matrix and translation vector.

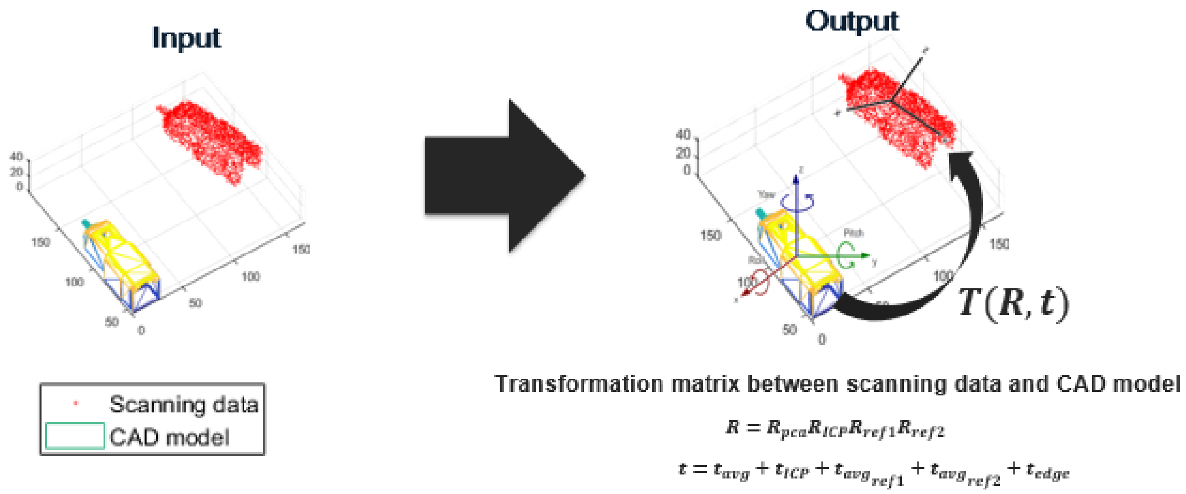


Figure III-3. Input and output of proposed processes

The pose of an object is defined in general by a 6-component vector $(x,y,z,\alpha,\beta,\gamma)^T$ (Mehrad *et al.*, 2013). Euler angles are expressing rotation of the object as a sequence of the 3 rotations around object's coordinate axes (Janota *et al.*, 2015). Rotation the object around its x-axis by angle Roll (marked α). Rotation the object around its y-axis by angle Pitch (marked β). Rotation the object around its z-axis by angle Yaw (marked γ). The rotation matrix **R** is a function of α, β, γ. Conversion from Euler angles to the rotation matrix can be expressed formula.

$$\mathbf{R} = \mathbf{R}_x(\alpha) \cdot \mathbf{R}_y(\beta) \cdot \mathbf{R}_z(\gamma) = \begin{bmatrix} c_\beta c_\gamma & c_\beta s_\gamma & -s_\beta \\ s_\alpha s_\beta c_\gamma - c_\alpha s_\gamma & s_\alpha s_\beta c_\gamma + c_\alpha s_\gamma & s_\alpha c_\beta \\ c_\alpha s_\beta c_\gamma + s_\alpha s_\gamma & c_\alpha s_\beta s_\gamma - s_\alpha c_\gamma & c_\alpha c_\beta \end{bmatrix}$$

where,

$$c_\alpha = cos\alpha \quad s_\alpha = sin\alpha$$

$$c_\beta = cos\beta \quad s_\beta = sin\beta$$

$$c_\gamma = cos\gamma \quad s_\gamma = sin\gamma$$

The translation vector **t** *z* expresses translational distance of coordinate along x, y and z axis

$$\mathrm{t} = [t_x \quad t_y \quad t_z]^T$$

Coordinate transformation is carried out by rotation matrix and translation vector. Following equation (3) shows dataset **p** is aligned by transformation. The result of transformation is **p'**

$$\mathbf{p}' = \boldsymbol{R} * \boldsymbol{p} + \boldsymbol{t}$$

Transformation matrix from design coordinate system that CAD model is exist to measurement coordinate system is derived from following process (Figure III-4). The whole process is composed of mainly two steps.

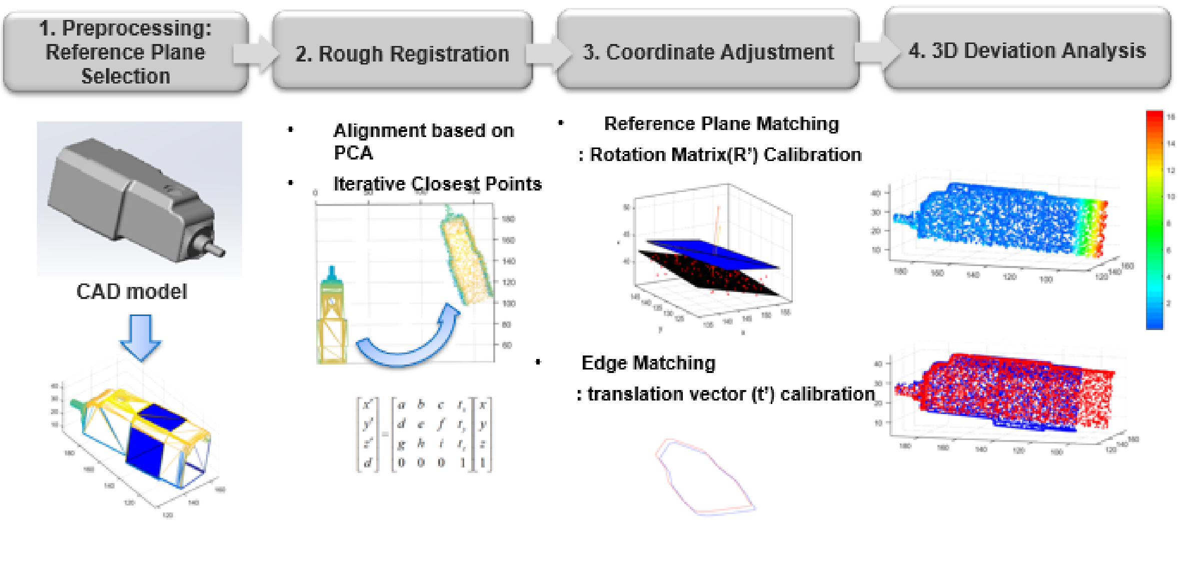


Figure III-4. Overview of registration and adjustment processes

Preprocessing should be performed before measurement, which is reference plane selection. This is necessary for reference plane matching proposed technique at coordinate adjustment method, which are third step. User select reference planes satisfying some condition in advance. This is preprocessing before performing measurement of object.

As a first step, measurement coordinate system is roughly registered on design coordinate system after gathering the scanning data. This process is decomposed into two stages. Scanning data and CAD model is aligned on XY plane based on Principal Components Analysis(PCA) and their centroid. Then, transformed datasets are aligned again by Iterative Closest Points(ICP).

Second step is coordinate adjustment for optimal transformation. This is main algorithm in this system. Reference plane matching is proposed for refinement of rotation matrix. Then, edge matching is introduced for translation vector adjustment.

Finally, 3D deviation analysis is carried out based on optimally matching result of scanning data and CAD model. The geometric deviation between the displace CAD model and the measurement data is showed by graph. Significant difference would be considered as defects

In conventional registration process, ICP is performed after feature-based matching, but in this thesis, ICP should be preceded in order to find a reference plane. We selected the reference plane in the CAD model in advance. However, we cannot detect directly which point set corresponds to the reference plane at the time data is scanned. Therefore, CAD model and scanning data are matched to position and posture as close as possible through two processes of rough registration. Then, in the scanning data, the points nearest to the reference plane on the CAD model are estimated as reference planes. After then, it is possible to perform coordinate adjustment about the rotation parameter by reference plane matching. Therefore, ICP should precede reference plane matching.

3.2.2 Preprocessing: Reference plane selection

There is a work to be done before measurements. This is preliminary work to use a method called reference plane matching to be applied to the coordinate adjustment step. The user must select a suitable face as the reference plane on the Mesh of the given CAD model in advance. Multiple plane could be selected as reference plane set of objects. User should choose an easy-to-detect plane that is representative of the object during the measurement (Yang *et al.*, 2010). In general, a stable wide plane must be selected. The following conditions must be satisfied:

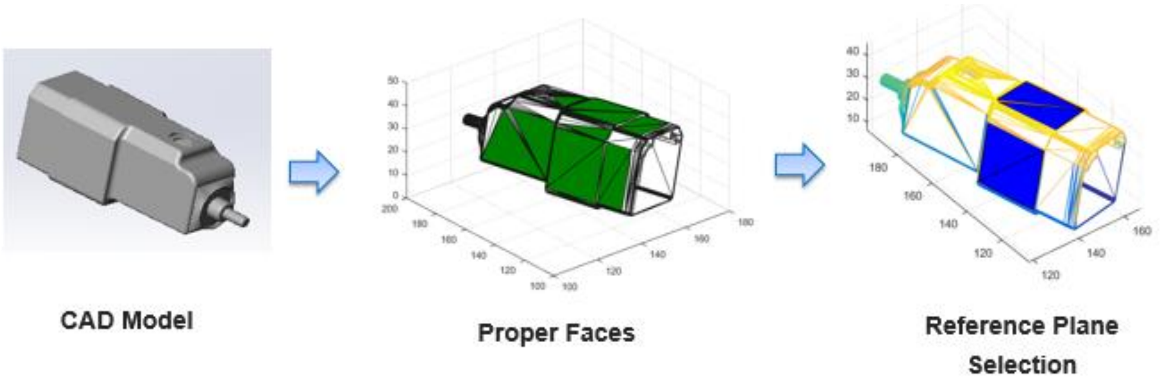


Figure III-5.Process of reference plane selection

Condition 1. Wide faces first

The larger the area, the more likely the plane will be detected even if the XYZ-plane shifting angles of measured object varied. Also, afterwards, the measured data is registered in the corresponding proximity plane, and a lot of points are likely to be registered on the reference plane. Amount of point affects the reliable plane approximation. The narrower the area of face, the higher the probability that the wrong point will be registered. So, it is vulnerable to noise since the weight of a point is increased when plane approximation. It may lead to irrelevant result. Therefore, it is recommended to select the reference plane by assigning priority to the face of the mesh in order of width

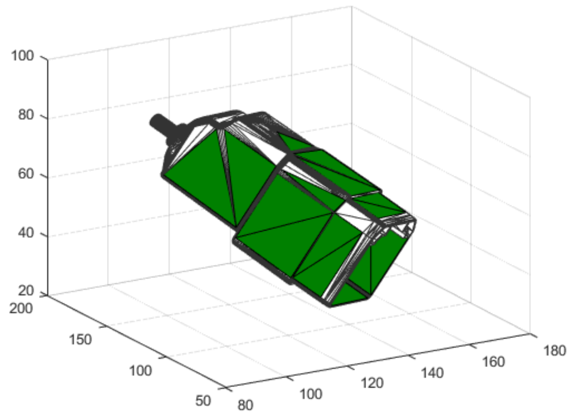


Figure III-6. 30 largest faces on CAD

Condition 2. External faces only

Depending on the shape of object, the CAD mesh may be composed of an inner surface that cannot be acquired a 3D point cloud from scanner. Unmeasurable faces must be excluded because they cannot be matched.

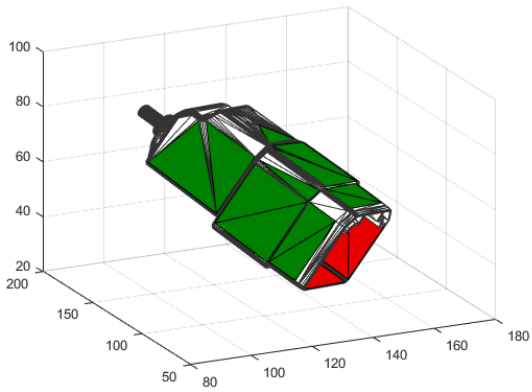


Figure III-7. Green is external faces; Red is inner faces

Condition 3. Exclusion of bottom faces.

Bottom data cannot be collected unless the object is turned over using the other device. As mentioned earlier, this system only collects data at once for speed, so bottom data cannot be collected. Therefore, the bottom face should also be excluded for the same reason as second condition.

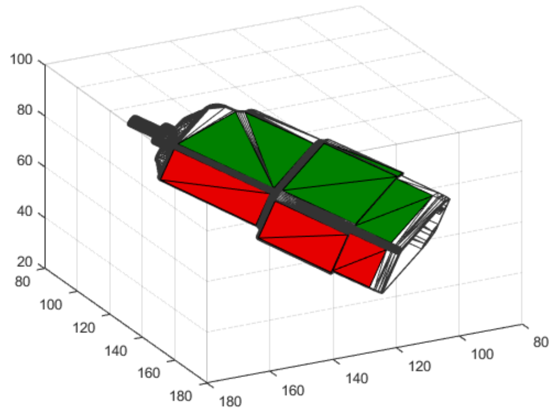


Figure III-8 Green is external faces; Red is bottom faces

Condition 4. Multiple reference plane selection

When selecting multiple faces, it is better to select the combination of faces that are always detected in the measured data at once. Combination of planes must be able to be gathered in a view since data is collected one for speed. In addition, the combination of the normal vectors of faces should not be paralleled each other. The larger the variation between normal vectors on each face, the more information can be used.

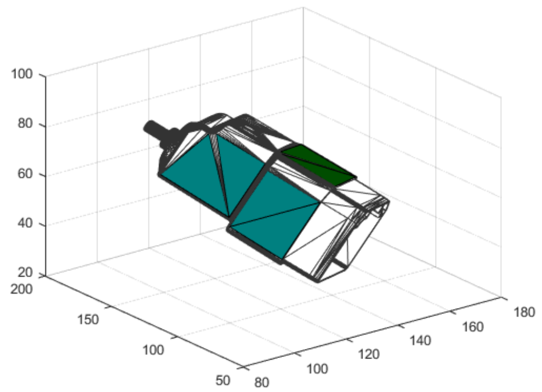


Figure III-9. Faces with same color have similar normal vector

The user would select a combination of reference planes that satisfying all of the above conditions. We will perform reference plane matching sequentially on planes that meets the above conditions most.

3.2.3 Rough registration

In this research, rough registration is carried out by two steps. Principal components analysis(PCA) is used to estimate rough transformation parameter by using principal components. Thus, for the more accurate transformation parameters, the iterative closest point (ICP) is used.

Step 1: PCA-based alignment

PCA is used for initial pose estimation of measured data comparing with CAD model. By applying PCA to the point cloud, the most representative basis of data can be extracted (F. Li *et al.*, 2017). Two point cloud from scanner and CAD model can be roughly aligned by the eigenvector of their covariance matrices.

A. PCA

Principal components analysis is a common statistical technique used to reduce the complexity of high volume data. The use of PCA make the large data easier to interpret (Mark, 2010). PCA reduce complexity without losing vital information (Makadia *et al.*, 2006). By applying PCA, the principal components are defined by the amount of variation of data. Figure III-10 shows an example of point cloud which PCA is applied.

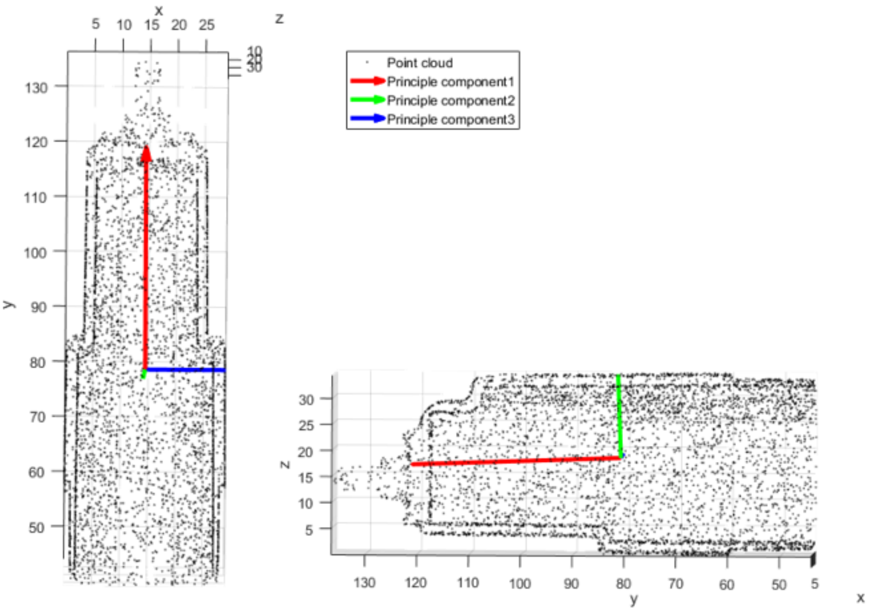


Figure III-10. Point cloud data with principal components in XY and YZ views

Direction of the principal axis is derived from three eigen vectors of the covariance matrix of dataset. A covariance matrix is assembly the variances and covariances of a data set. Principal components analysis calculates the principal components by decomposing the covariance matrix. The covariance matrix identifies how two variables related each other. The covariance matrix S for given N points $x_i = [x_i \quad y_i \quad z_i], \mathrm{i} = 1, \ldots, \mathrm{N}$ is defined as

$$\mathrm{S} = \frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})(x_i - \bar{x})^T$$

where,

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$$

To find the direction and magnitude of the principal components, Eigenvalue Decomposition can be used on covariance matrix S. The eigenvectors mean the direction of the principle components of dataset. The eigenvalues mean the standard deviation of data along that principle components

The eigenvalues, $\lambda = [\lambda_1 \quad \lambda_2 \quad \lambda_3]$,where $\lambda_1 > \lambda_2 > \lambda_3$ and eigenvectors U= $[u_1 \quad u_2 \quad u_3]$, of covariance matrix S are defined as

$$\mathrm{SU} = \lambda\mathrm{U}$$

Covariance matrix S can be factorized as

$$\mathrm{S} = \mathrm{U}\Lambda\mathrm{U}^{\mathrm{T}}$$

where,

$$\Lambda = \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & \lambda_3 \end{bmatrix}$$

We can get a rotation between measured data and CAD model data using direction of principal axis of point cloud. The rotation matrix **R** can be derived from

$$\mathbf{R} = \mathrm{U}_{\mathrm{CAD}} U_{Data}^{-1}$$

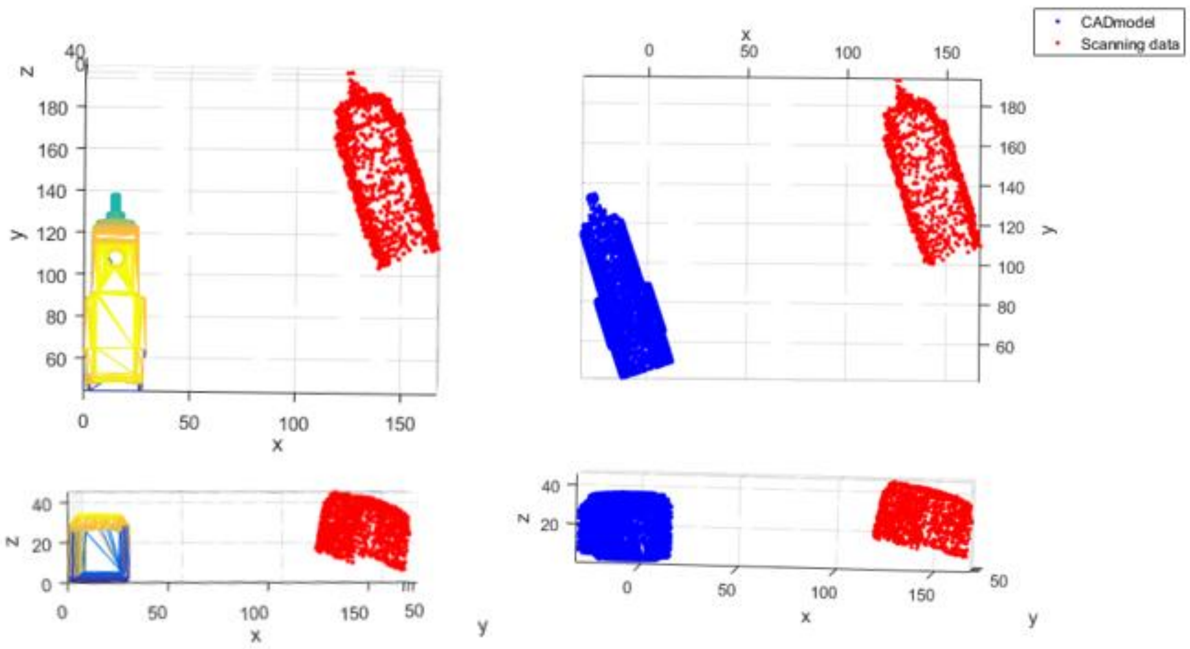
Where $\mathrm{U}_{\mathrm{CAD}}$ is eigenvector of CAD data and $\mathrm{U}_{\mathrm{Data}}$ is eigenvector of measured data

B. 3D Registration by principal component of data

In order to apply principal components analysis to alignment, CAD mesh should be converted to point cloud data as shown in figure III-11. Generally, all three principle components are used for calculating rotation matrix using PCA as shown above equation.

Our system scan object only once, so it is hard to get the data from bottom surface of object. However, a point cloud generated from a CAD mesh includes a bottom surface. A method of removing directly the underside of a point cloud generated from a CAD mesh is also considered, but the area that cannot be collected may be different according to the shifting angle of the object. It may affect direction of principal components and leads to wrong result.

Therefore, in this paper, a rotation matrix is obtained by using only first principal component vector. Since only first principal component vector in XY plane is used, only the rotation about z-axis, that is, the rotation on the XY plane, is considered



(a) (b)

Figure III-11 (a) CAD model with scanning data (b) Point cloud generated from CAD and scanning data

Two point cloud set, which are scanning data and CAD data, are projected on XY plane. Then 3D point cloud data become 2D data sets. Principal component analysis is performed on these 2D data. Let's notate 2D projection data from scanning as $P_{\mathrm{2D.scan}}$ and 2D projection data from CAD as $P_{\mathrm{2D.CAD}}$. Two principal components would be derived from each 2D projection data. Each first principal component would be used for rotation matrix. $\vec{v}_{scan}$ is the unit vector of first principal component of scanning data. $\vec{v}_{CAD}$ is the unit vector of first principal component of CAD data.

Rotation matrix **R** that rotate unit vector $\vec{v}_{CAD}$ onto unit vector $\vec{v}_{scan}$ derived from following steps

$$\mathbf{R_{3D}} = \mathrm{I} + [v]_{\times} + [v]_{\times}^{2}\frac{1-c}{s^{2}}$$

where,

$$v = \vec{v}_{CAD} \times \vec{v}_{scan}$$

$$s = \|v\| \text{ (sine of angle)}$$

$$c = \vec{v}_{CAD} \cdot \vec{v}_{scan} \text{ (cosine of angle)}$$

$[v]_{\times}$ is the skew-symmetric cross product matrix of v

$$[v]_{\times} \stackrel{\text{def}}{=} \begin{bmatrix} 0 & -v_3 & v_2 \\ v_3 & 0 & -v_1 \\ -v_2 & v_1 & 0 \end{bmatrix}$$

For the 2D case, the formula can be simplified given $\vec{v}_{scan} = (x_1, y_1, 0)$ and $\vec{v}_{CAD} = (x_2, y_2, 0)$. Following rotation matrix become rotation matrix from PCA applying on 2D data sets.

$$cos\theta = \vec{v}_{scan} \cdot \vec{v}_{CAD} = x_1x_2 + y_1y_2$$

$$sin\theta = \vec{v}_{scan} \times \vec{v}_{CAD} = x_1y_2 - x_2y_1$$

$$\mathbf{R_{2D}} = \begin{pmatrix} x_1x_2 + y_1y_2 & x_1y_2 - x_2y_1 & 0 \\ -(x_1y_2 - x_2y_1) & x_1x_2 + y_1y_2 & 0 \\ 0 & 0 & 1 \end{pmatrix} = \mathbf{R_{PCA}}$$

The translation vector **t** can be derived by centroid of two data set. The centroid are 3×1 column vectors.

$$\mathbf{t} = centroid_{Scan} - centroid_{CAD}\mathbf{R_{PCA}} = \mathbf{t_{avg}}$$

where,

$$centroid_{Scan} = \frac{1}{N}\sum_{i=1}^{N} P_{scan}$$

$$centroid_{CAD} = \frac{1}{N}\sum_{i=1}^{N} P_{CAD}$$

Therefore, CAD data would be registered by rotation matrix and translation vector as shows in figure III-12

$$P'_{CAD} = \mathrm{P}_{\mathrm{CAD}}\boldsymbol{R_{PCA}} + \boldsymbol{t_{avg}}$$

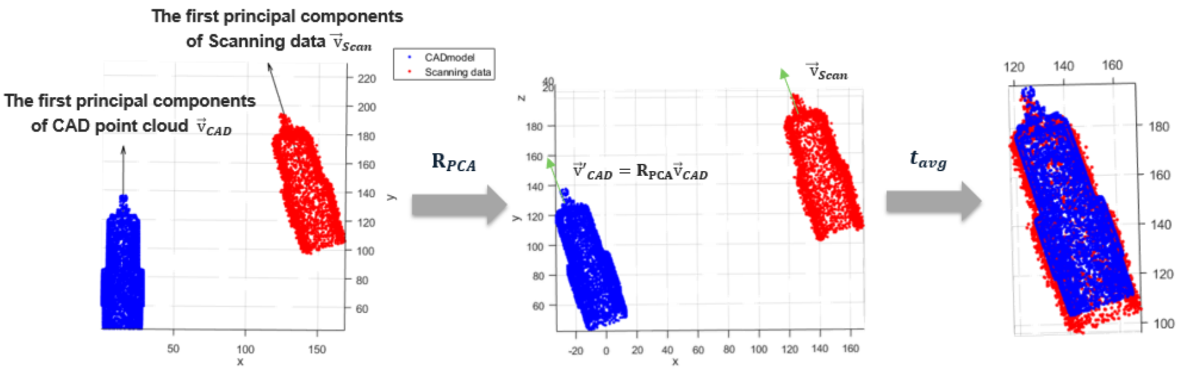


Figure III-11. Process of PCA based alignment

Step2: ICP-based alignment

ICP is used for fine registration to improve the previous pose estimation from PCA-based alignment. It is a point to point approach requiring initial guess. More accurate rotation and translation parameters are estimated by minimizing the Euclidean distance corresponding point pairs.

A. ICP

ICP is widely used algorithms for fine registration between a set of data points to a set of model points (Besl *et al.*, 1992). Its result shows high accuracy with simple approach. The main advantage of ICP is it does not need geometrical feature or descriptor for matching since it based on point to corresponding point matching (Bærentzen *et al.*, 2012).

To begin with ICP, it requires initial guess which is starting point. Initial guess affects a lot to registration result since ICP does not work if two input data are not close enough (Mark, 2010). Therefore, alignment based on PCA was preceded. Using the starting point, the ICP repetitively refines a pose estimation until two data set converge criterion.

ICP algorithm computes six DOF pose vector $[x, y, z, \alpha, \beta, \gamma]$. which consists of three translation components x, y, z and three rotation components α, β, γ. ICP is performed as following main steps

1. Generate correspondence between two data sets that each point corresponds with the nearest point in the other data set. C is closest point operator.

$$\mathrm{Y} = \mathrm{C}(P_{CAD}, P_{Scan}) = \min_{y_i \in P_{Scan}} \| P_{CAD.i} - y_i \|$$

2. Compute new transformation parameters by minimizing the Euclidean distance between corresponding point pairs. Typically, the mean square error(MSE) is used as criterion function, but the other criterion function can be used as well.

$$[\mathbf{R_{ICP}}, \mathbf{t_{ICP}}] = \underset{\mathbf{R},\mathbf{t}}{\operatorname{argmin}} \sum_{i=1}^{N} \frac{1}{N} \| \mathbf{R_{ICP}} P_{CAD} + \boldsymbol{t_{ICP}} - P_{scan} \|^2$$

3. Apply registration using rotation matrix R and translation vector t. It means new point cloud $\mathrm{P}'_{\mathrm{CAD}}$ has been found

$$\mathrm{P}'_{\mathrm{CAD}} = \mathbf{R} P_{CAD} + \boldsymbol{t}$$

4. Iterate 1~3 until meeting one of below conditions

- The number of iteration reach at the maximum
- The error falls bellows certain threshold τ

In summary, input and output of ICP algorithm is shown following figure III-13

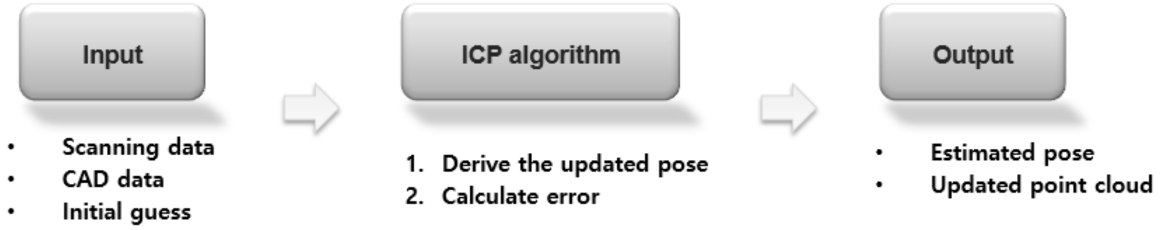


Figure III-12. ICP algorithm

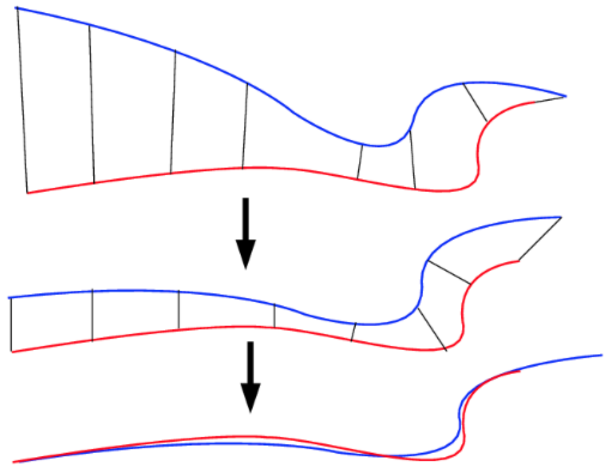


Figure III-13. Illustration of the ICP method to align two lines (Smistad *et al.*, 2015)

B. Implementation of ICP

The original ICP, which is described above section, assumed that there is no outlier on data and two data set can be overlapped 100% accuracy. It is not applicable since measured data and point data generated from CAD data cannot be same. Therefore, there are a lot of research on advanced algorithm of ICP, which is so robust to noise that improve this limitation. Among them, IRLS-ICP is implemented in this paper, which is published recently (Bergström *et al.*, 2017).

IRLS-ICP is abbreviated of iteratively reweighted least square-ICP. This algorithm proposed a new criterion function on ICP. A robust criterion function ϱ(r) is used for reducing undesired influence of data with gross errors on the estimation. Therefore, criterion function is

$$[\mathbf{R_{ICP}}, \mathbf{t_{ICP}}] = \underset{\mathbf{R},\mathbf{t}}{\operatorname{argmin}} \sum_{i=1}^{N} \varrho \| \mathbf{R_{ICP}} P_{CAD} + \boldsymbol{t_{ICP}} - P_{scan} \|$$

where

$$\varrho(\mathrm{r}) = \frac{\kappa_{Ca}^2}{2} \ln(1 + \left(\frac{r}{\kappa_{ca}}\right)^2)$$

where

$$\kappa_{ca} = 4.3040$$

As mentioned in the previous section, alignment based on PCA was used as initial guess and ICP was performed. When only PCA is applied, only the z axis rotation is considered, so that the remaining x and y axis rotation angles, pitch and yaw, are not matched. After applying the ICP, you can see a more precise matched on all three axes (figure III-15).

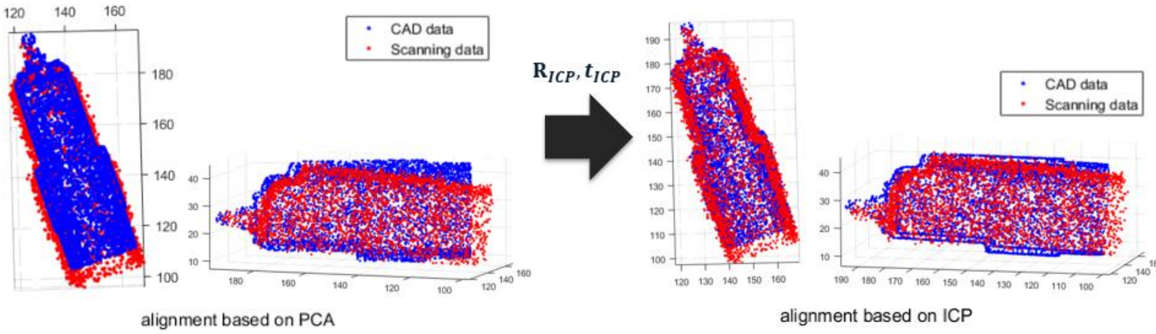


Figure III-14. Result of ICP based alignment

3.2.4 Coordinate adjustment

The general registration process for matching point clouds consists of coarse registration after feature extraction and fine registration using ICP that is point based algorithm for more precise matching However, since the target system of this paper needs to perform the measurement, a more precise matching method than the ICP only is needed.

Therefore, coordinate adjustment step was introduced for more precise matching between two coordinate systems, which are measured coordinate system and design coordinate system. First, a reference plane matching method is introduced to correct the rotation matrix that determines the shift angles of the x, y, and z axes. We optimized the roll, pitch, and yaw and then adjusted the translation by applying the method called edge matching.

Step 1: Reference plane matching

Reference plane matching is a method of matching two plane, which are reference plane selected from CAD mesh and corresponding plane extracting from measured data. Ideally aligned, the two planes are the same plane, so there should be no difference in the normal vector of the planes. We use this assumption to correct the rotation matrix more precisely. This is done through the following process.

A. Extract reference plane from scanning data

Through rough registration process, scanning data and CAD data are almost overlapped. Therefore, corresponding CAD mesh face to the plane constituting point in scanning data is more likely to be the face closest to the point and the mesh face. Using this point, we calculate the face with the closest Euclidean distance between each point and the CAD mesh face, and register the point on the face. Point sets registered on reference plane would be used in next step.

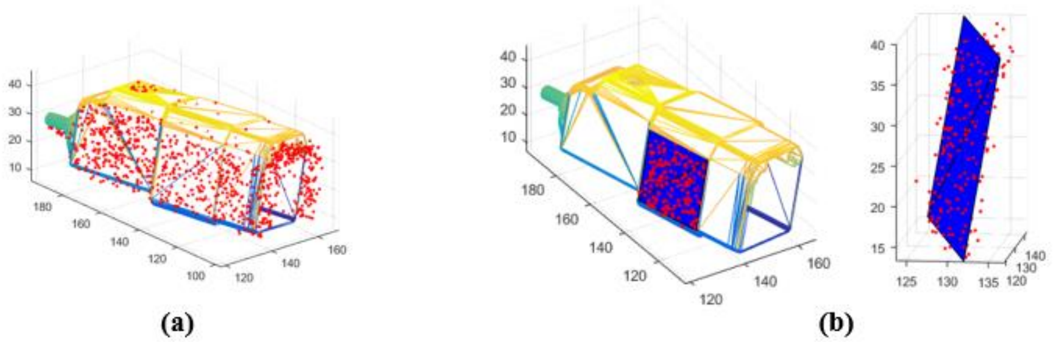


Figure III-15. (a) Aligned CAD and scanning data (b) Point sets registered on reference plane

B. Plane fitting using PCA

Plane approximation is performed based on the points registered in the reference plane. Plane fitting using PCA was used to determine the best fitting plane from location in a point cloud. Given a set of 3D points, we can find out a plane that describe this set of point(Sanchez *et al.*, 2012).

PCA returns two orthogonal principal component vectors when performing PCA on a two-dimensional data set, and PCA on three-dimensional points returns three orthogonal principal component vectors (Stegmann *et al.*, 2002). If the first principal component vector e_1 and the second principal component vector e_2 are derived from PCA, then the approximate plane equation is as follows.

$$(e_1 \times e_2) \cdot (x - m) = 0$$

where

$$x = (x, y, z), \qquad m = avg(x, y, z)$$

$$e_1 : first\ principal\ component\ vector$$

$$e_2 : Second\ principal\ component\ vector$$

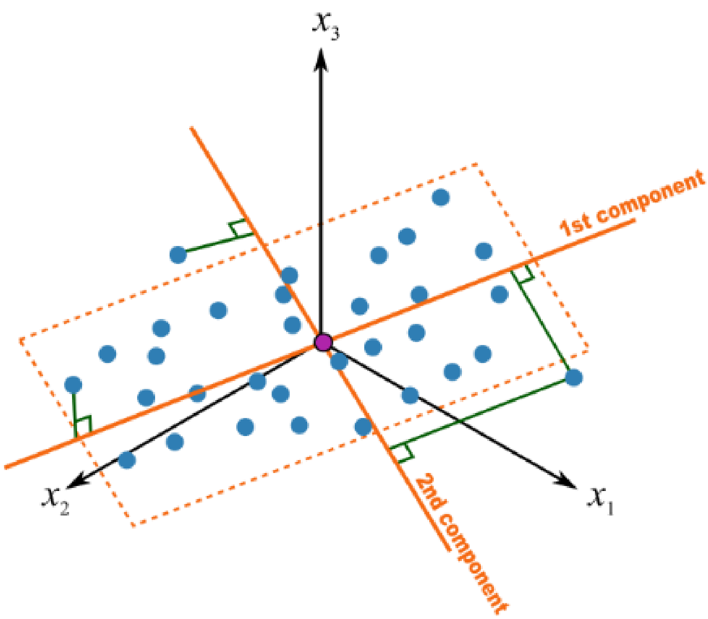


Figure III-16. Best fitting plane using PCA (Dunn, 2017)

C. Transformation

Now, we can compare normal vectors between reference plane in CAD ($\vec{n}_{CAD}$) and approximate plane from scanning data($\vec{n}_{scan}$). The equation derived in 3.2.3.1 alignment based on PCA is used to calculate rotation matrix. Rotation matrix $\mathbf{R}_{ref}$ that rotate unit normal vector $\vec{n}_{CAD}$ onto unit vector $\vec{n}_{scan}$ is

$$\mathbf{R}_{ref} = \mathrm{I} + [v]_{\times} + [v]_{\times}^{2} \frac{1-c}{s^{2}}$$

where,

$$v = \vec{n}_{CAD} \times \vec{n}_{scan}$$

$$s = \|v\| \text{ (sine of angle)}$$

$$c = \vec{n}_{CAD} \cdot \vec{n}_{scan} \text{ (cosine of angle)}$$

$[v]_{\times}$ is the skew-symmetric cross product matrix of v

$$[v]_{\times} \stackrel{\text{def}}{=} \begin{bmatrix} 0 & -v_3 & v_2 \\ v_3 & 0 & -v_1 \\ -v_2 & v_1 & 0 \end{bmatrix}$$

The translation vector $\mathbf{t}$ can be derived by centroid of two data set.

$$\mathbf{t} = centroid_{scan_{ref}} - centroid_{CAD_{ref}} \mathbf{R}_{ref} = \mathbf{t}_{\mathbf{avg}_{ref}}$$

Therefore, CAD data would be registered by rotation matrix and translation vector as shows in figure III-18

$$P'_{CAD} = \mathrm{P}_{\mathrm{CAD}} \boldsymbol{R}_{ref} + \boldsymbol{t}_{avg_{ref}}$$

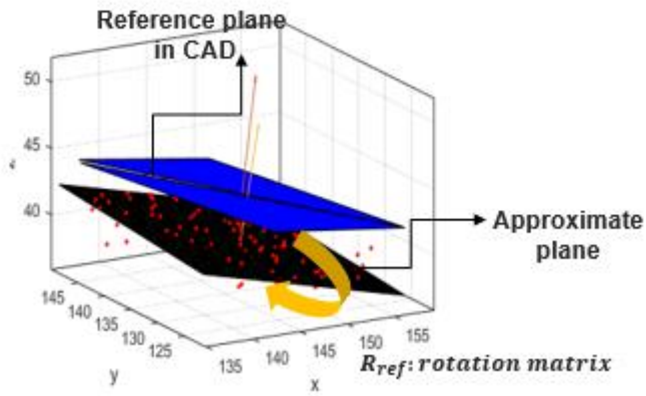


Figure III-17. Reference plane matching using difference between two normal vectors

Repeat steps 1 to 3 when multiple reference planes are selected. It is recommended that the plane approximation be performed in a planar order with a wider area and higher reliability of the plane approximation.

Step 2: Edge matching

Edge matching is a method proposed to translation vector adjustment for precision. As can be seen in the figure III-19, the data obtained by performing the rough registration and reference plane matching are well aligned at the x,y and z shift angle, but it seems necessary to adjust the translation slightly. It can be seen that the difference is clearly showed when the data is projected in 2D. The difference between the centroid of two data was used to derive the translation vector while performing reference plane matching, which seems to be insufficient for precise translation matching.

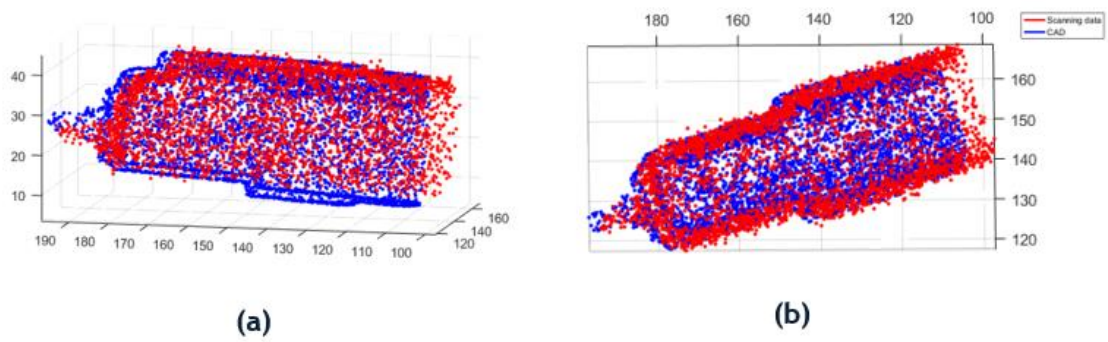


Figure III-18. (a) Result of rough registration in 3D view (b) in 2D view (XY plane)

Therefore, it is assumed that the variation of roll, pitch, and yaw between CAD-scanning data are calculated precisely by using reference matching, and then the edge matching is performed in order to secure the precision of translation. The following methods were used to satisfy both computational time and accuracy.

First, the reference plane matching is performed to project the point cloud data and the scanning data of the CAD which matched to some degree precisely on the XY plane. Then, extract boundaries based on projected data. The points that represent the boundary of each point set are called the boundary. Since the measured object is a rigid body, information is sufficient even if the boundary is extracted.

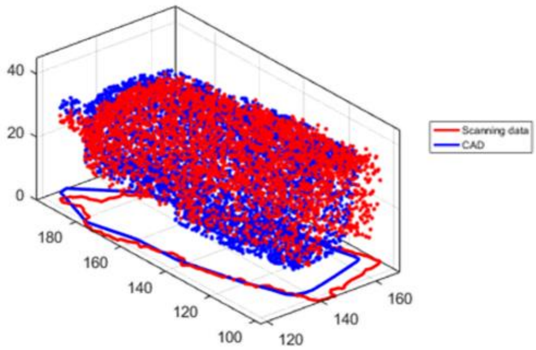


Figure III-20. Boundary extraction

The corresponding points having the minimum distance among the points constituting the boundary of the scanning data are searched for each point constituting the boundary of the CAD data. Then, a translation vector parameter that minimizes the sum of the minimum distances should be obtained.

$$C(b_{CAD}, b_{Scan}) = \underset{b_{CAD}, b_{Scan}}{\operatorname{argmin}} \; \mathrm{d}_{\min} = \underset{b_{CAD}, b_{Scan}}{\operatorname{argmin}} \; \| b_{CAD}(x_{CAD}, y_{CAD}) - \mathrm{b}_{\mathrm{Scan}}(x_{Scan}, y_{Scan}) \|$$

where,

$$b_{CAD}: x, y \; point \; set \; constituting \; boundary \; of \; CAD$$

$$b_{Scan}: x, y \; point \; set \; constituting \; boundary \; of \; Scannind \; data$$

$$d_{min}: Minimun \; distacne \; between \; corresponding \; points$$

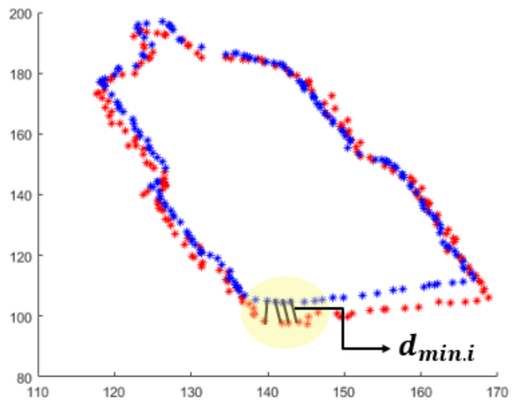


Figure III-21. The corresponding points having the minimum distance among the points in boundary of CAD and measured data

The Gird search algorithm was used for this purpose. The Grid search is a method of dividing the hyperparameter space into grid form, calculating the validation error for each grid point, and selecting the hyperparameter that represents the lowest error among all grid points (LaValle *et al.*, 2004). When using Grid search, you should set the appropriate range and interval. The range of the grid is the range of the boundary of the CAD data and the boundary of the corresponding scanning data. Also, a value corresponding to 1/2 of the target error tolerance was used as the interval.

$$[\Delta x, \Delta y] = \underset{\Delta x, \Delta y}{\operatorname{argmin}} \sum_{i=1}^{n} d_{min.i}$$

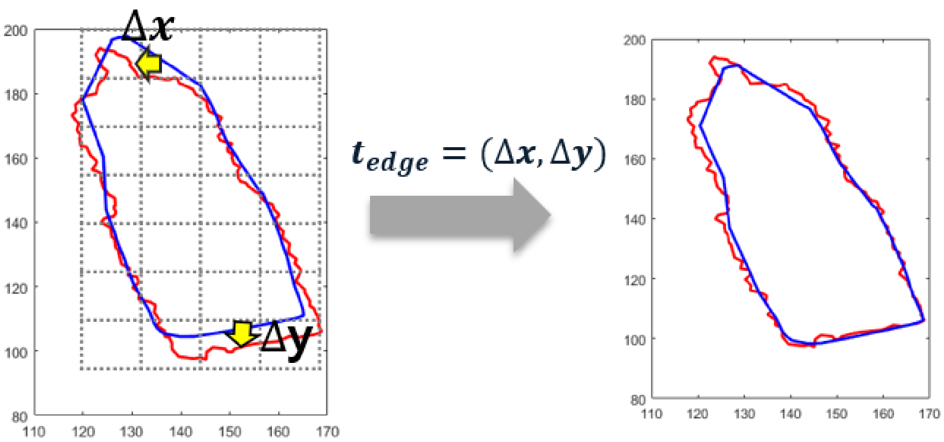


Figure III-9. Translation using edge matching in XY plane

As a result, we can see that the 2D boundary data are well matched for translation. Applying this translation parameter to 3D data shows that it is precisely matched. The Z value parameter is the difference between the maximum value of each data.

$$\mathbf{t_{edge}} = [\Delta x, \Delta y, \Delta z_{max}]$$

Where

$$\Delta z_{max} : differecne\ between\ maximum\ z\ value\ in\ CAD\ and\ Scanning\ data$$

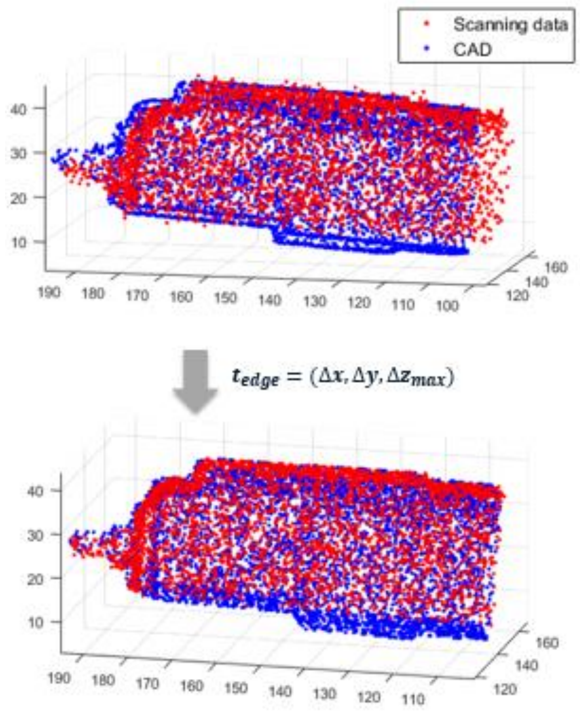


Figure III-23. Edge matching in 3D data

3.2.5 3D Deviation analysis

Through two stages of rough registration and coordinate adjustment, CAD data and scanning data are now perfectly matched. In other words, precision alignment of the design coordinate system and the measurement coordinate system is performed, and 3D deviation analysis becomes possible (Steger *et al.*, 2017). 3D deviation is the distance estimation between the scanning data and the CAD mesh.

The minimum distance from the CAD mesh to the measured point is expressed as a deviation. The deviation is obtained from minimum among following three values. 1. Linear distance between measured point and mesh face 2. Linear distance between measured point and mesh edge 3. Minimum distance between measure point and point generated from CAD data.

Figure III-24 (b) shows the deviation distribution visually by using color. If the deviation indicates a value greater than or equal to the specified tolerance, the product may be determined to be defective.

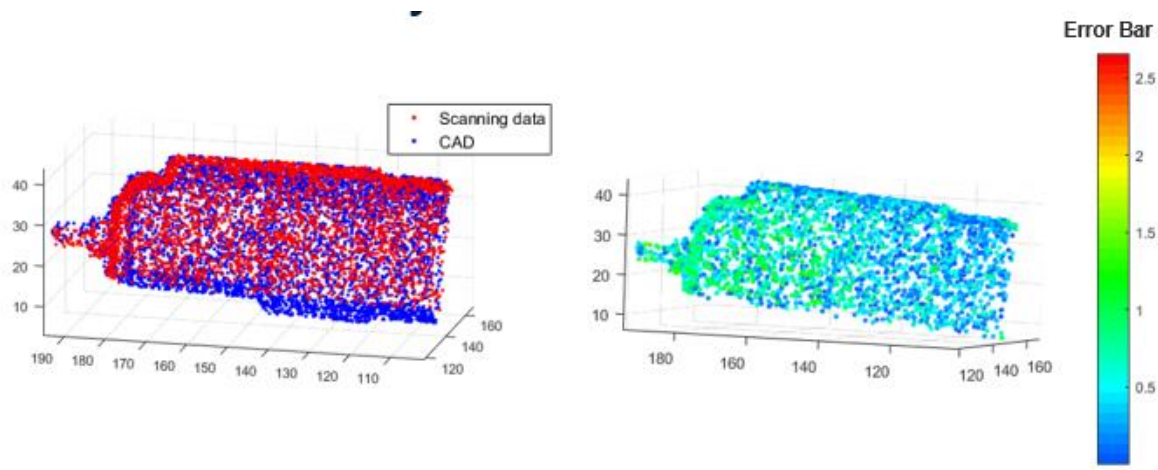


Figure III-24. 3D deviation graph

3.3 Summary

Coordinate recognition method was proposed for 3D deviation analysis of randomly positioned object with variation on X, Y, and Z translation along the X, Y, and Z directions and rotation angle around the X, Y, and Z axes comparing to reference CAD model. It is a fully-automated and real-time inspection system without physical calibration for home positioning of objects given reference CAD model and its point cloud data.

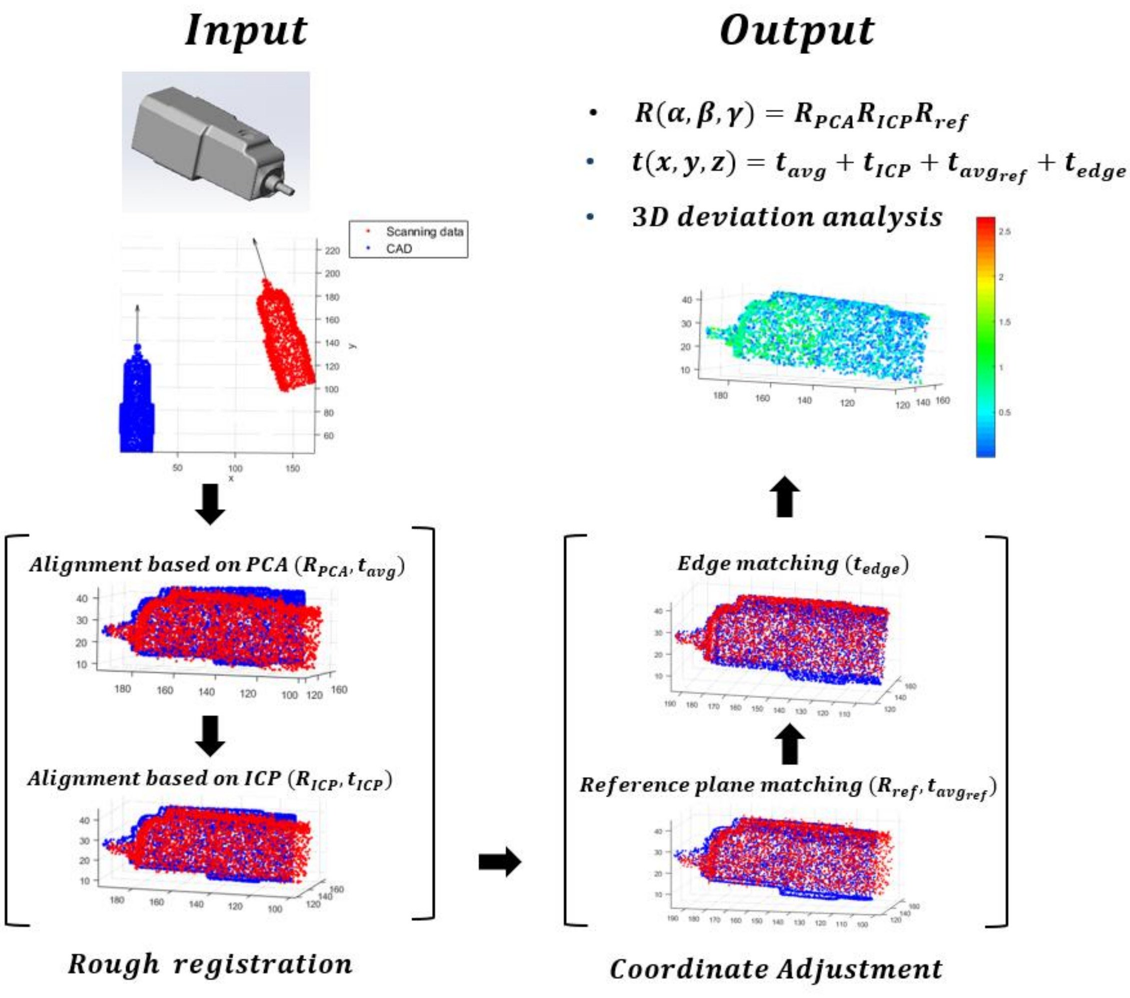


Figure III-25. 3D deviation analysis by coordinate recognition of randomly positioned objects

The system automatically calculates the rigid transformation by combining rotation matrix and translation vector extracted from whole process. We can estiamte transformation parameter, which are roll,pitch,yaw by solving below equation

$$R(\alpha,\beta,\gamma) = R_x R_y R_z = \begin{pmatrix} 1 & 0 & 0 \\ 0 & cos\alpha & -sin\alpha \\ 0 & sin\alpha & cos\alpha \end{pmatrix}\begin{pmatrix} cos\beta & 0 & sin\beta \\ 0 & 1 & 0 \\ -sin\beta & 0 & cos\beta \end{pmatrix}\begin{pmatrix} cos\gamma & -sin\gamma & 0 \\ sin\gamma & cos\gamma & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

$$= \begin{pmatrix} cos\beta cos\gamma & -cos\beta sin\gamma & sin\beta \\ sin\alpha sin\beta cos\gamma + cos\alpha sin\gamma & -sin\alpha sin\beta sin\gamma + cos\alpha cos\gamma & -sin\alpha cos\beta \\ -cos\alpha sin\beta cos\gamma + sin\alpha sin\gamma & cos\alpha sin\beta sin\gamma + sin\alpha cos\gamma & cos\alpha cos\beta \end{pmatrix}$$

We can compare how accurate the results are if we know the ground truth of transformation parameters. Measured object on the figure III-26 was rotated by roll=4.5°, pitch = 9°, yaw= 18° and measurement error by device is 1mm and there is no defect. Translation parameter is derived directly by comparing centroid of initial point set with transformed point set. Maximum deviation was 1.6mm and it is under target tolerance 2mm from twice measurement error 1mm. Therefore, translational parameters were estimated precisely with acceptable tolerance. Accumulated angular error on roll, pitch, yaw was under 1°. It shows high precision compared to result applying just coarse registration and ICP.

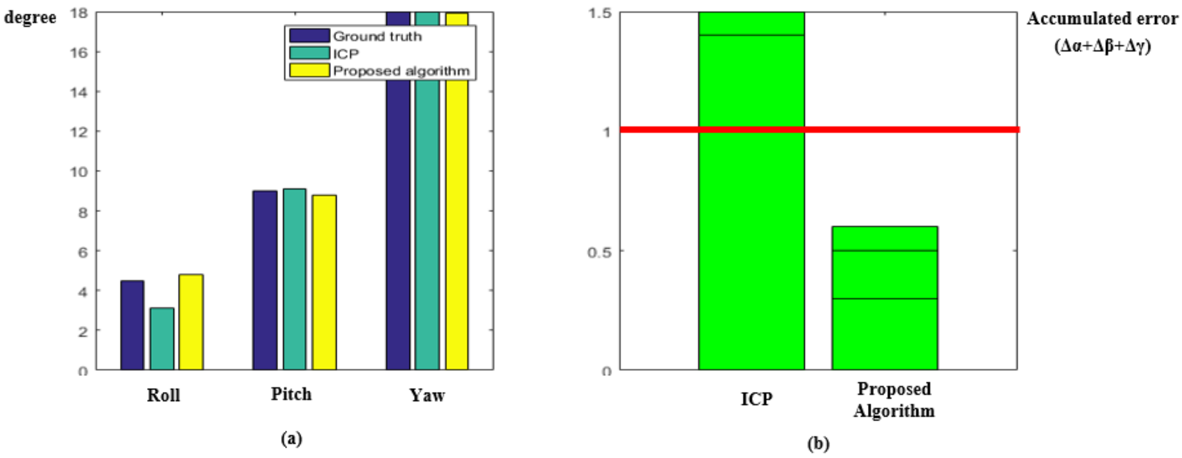


Figure III-26.(a) Shift angle (roll, pitch, yaw) (b) Accumulated error

IV. Experiments

4.1 Experiment Setup

The proposed algorithm has been tested against on toy product whose dimension is 30×140×40mm. It is a housing of electric tooth brush (ETH) already used above chapter to explain procedure of algorithm. As mentioned above, two reference planes are selected. The objective of the inspection is to determine whether the surface of the object has not a defect by comparison with CAD model

There are three kinds of defects on ETH. One is 20mm longer than original shape, which is called Defect A, the other is 4.5mm thinker on right and left side of product, which is called Defect B. Two kinds of defects are due to machining error. When defect A is occurred, the product cannot be assembled with other parts. In Defect B, the portion gripped by hand becomes thick, which makes the user inconvenient for brushing. This means a decreased in quality. Therefore, quality inspection should be conducted on the following two types of defects. Defect C is similar with defect A but error deviation of defect C is only 2mm which is the minimum tolerance for this registration.

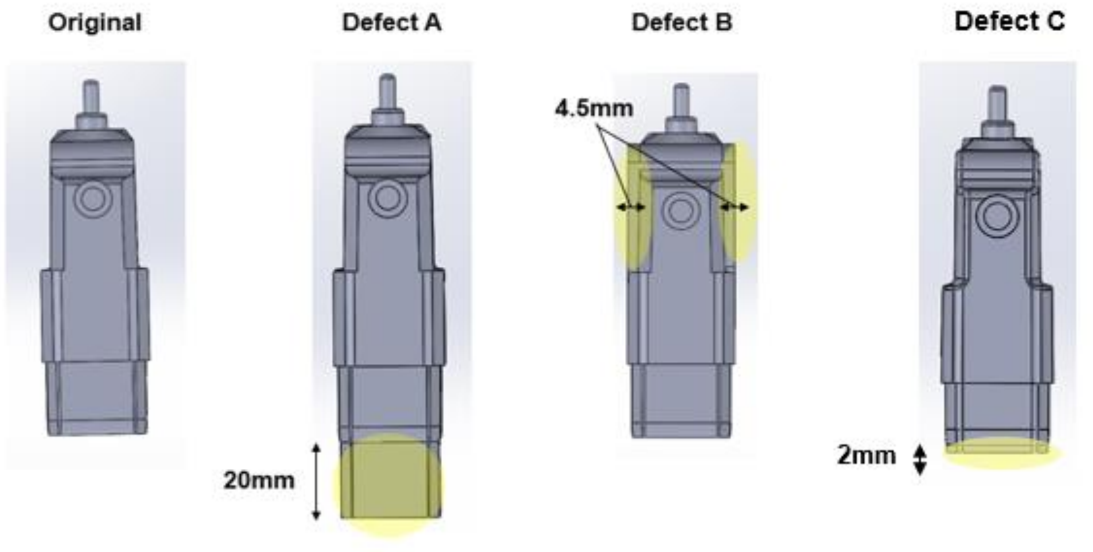


Figure IV-1. Comparison Defect A, B, C with original CAD model

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Experiments were conducted to determine whether the algorithm is robust to variation on shift angle, whether the results were different depending on the measurement error, and whether the defect was well detected

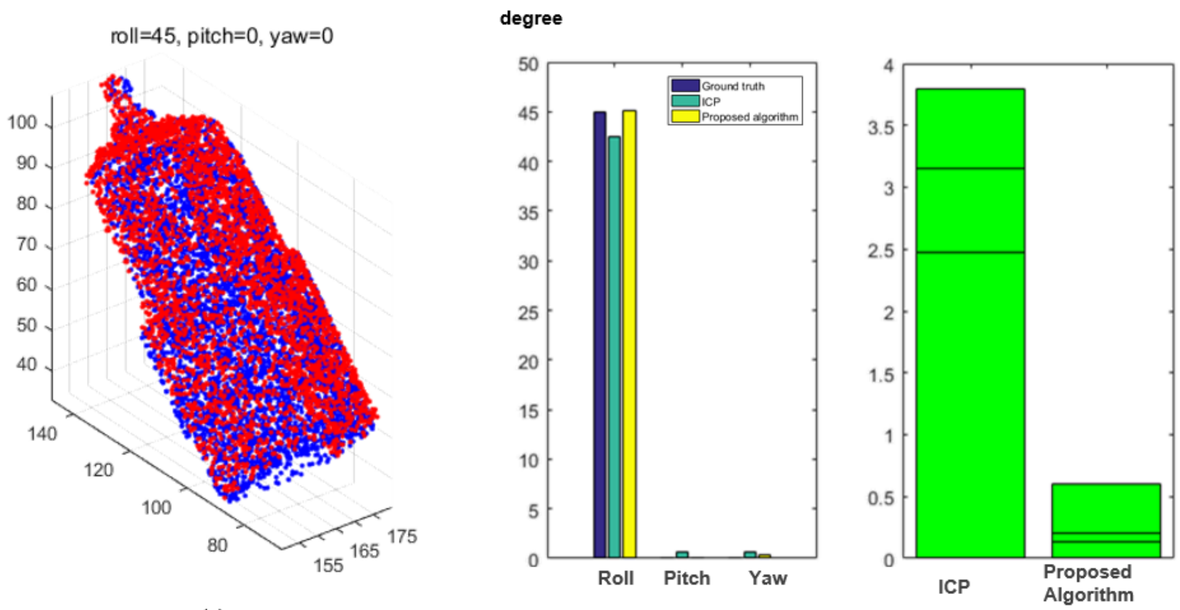
4.2 Experiment Results

4.2.1 Variation in the shift angle

Experiments were carried out with different variations of roll, pitch, and yaw for normal products without defects. In this case, the measurement error is 1 mm.

First, we tried to make an angular shift only for one axis among roll, pitch, and yaw. In other words, only one axis is rotated specific degree and the other axis is aligned normally, 0 degree. The last figure IV-5 shows the random variation of all three axes

The proposed registration process can work within the acceptable range for in-process measurement. In this experiment, the maximum value of roll is set to 45 degree, maximum value of pitch is 35 degree and maximum value of yaw is 45 degree. Therefore, the experiment about variation on shift angle was conducted under these conditions.



(a) (b) (c)

Figure IV-2. Angular variation only around the x axis

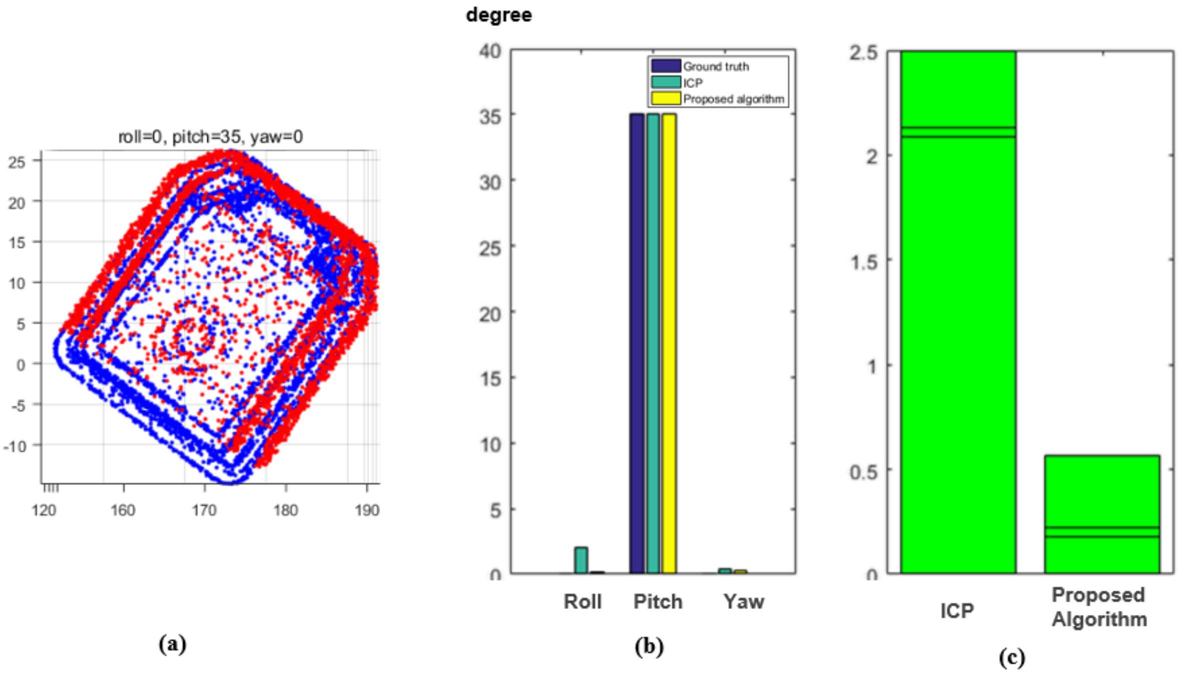


Figure IV-3. Angular variation only around the y axis

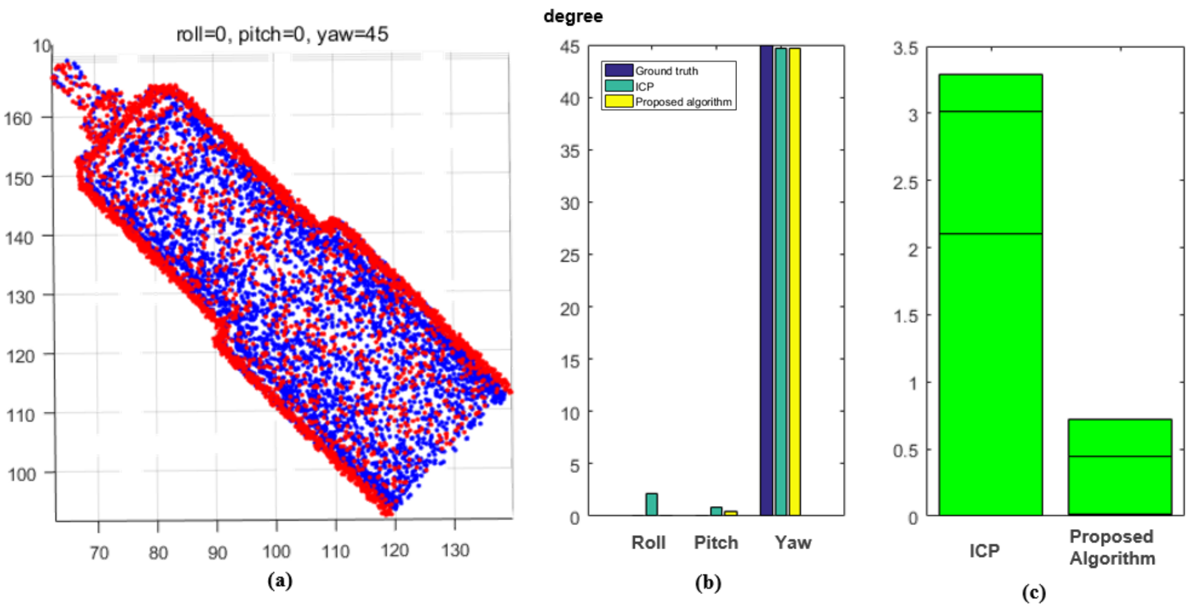


Figure IV-4. Angular variation only around the z axis

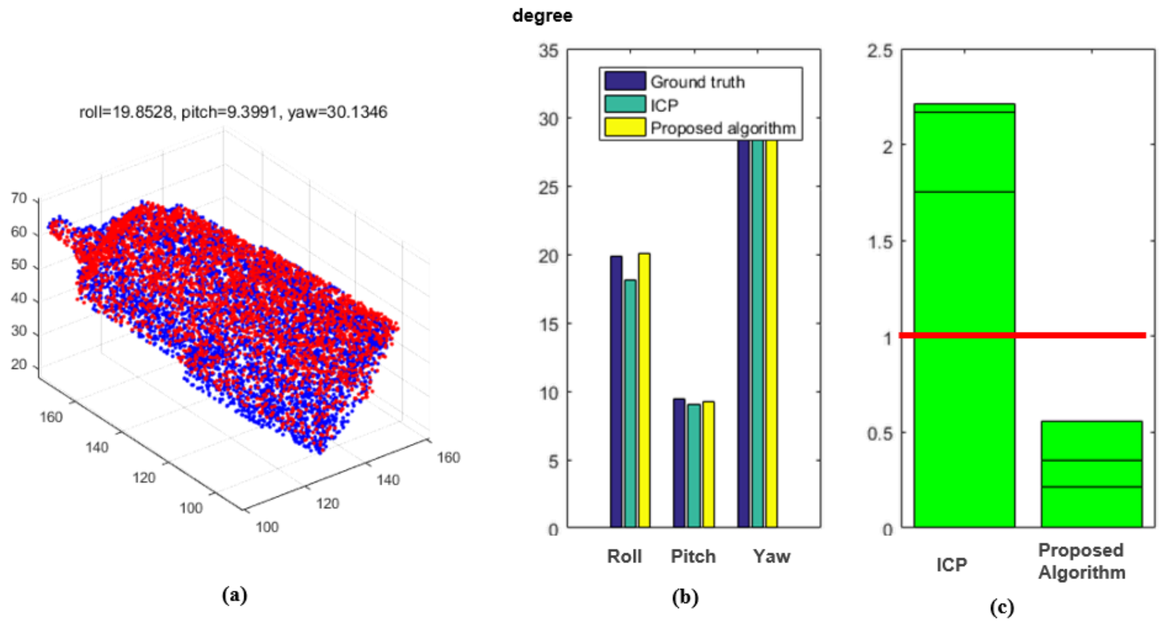


Figure IV-5. Angular variation around all axes

In each figure IV-2~5, (a) is the result of matching scanning data with CAD model. (b) compares the estimated values of roll, pitch, and yaw by applying Rough registration only up to the ICP and the result of applying the coordinate adjustment to the proposed algorithm. (c) shows the cumulative error values of roll, pitch, and yaw estimated through the proposed algorithm and only to the ICP. With proposed algorithm, it is shown that cumulative error value falls to less than 1˚ as a whole.

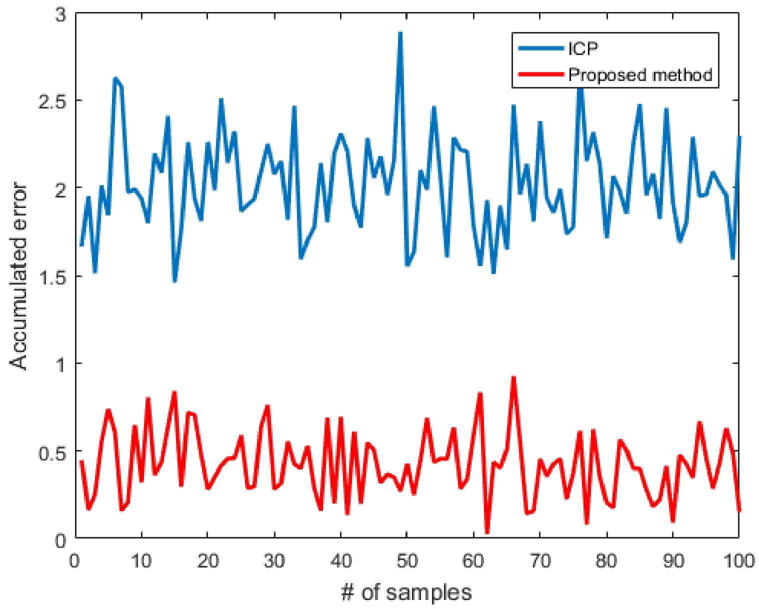


Figure IV-6. Result of 100 times experiments with angular variation around all axis

Figure IV-6 is graph for 100 experiments with angular variation around all axis such as case of figure IV-5. Angular variation is randomly generated under acceptable range, which are $0^{\circ}<\alpha<45^{\circ}$, $0^{\circ}<\beta<35^{\circ}$ and $0^{\circ}<\gamma<45^{\circ}$. Accumulated error from proposed registration method are always smaller than error from ICP. Average of accumulated error of ICP was 2.0245 degree and it is almost 5 times of average value of proposed method 0.4246.

These differences can have significant effect on the result of surface inspection. A normal product can be misdetermined as a defect by inaccurate registration. As shown in Figure IV-7, 3D deviation graph of proposed registration (a) shows all area of normal product is blue and it means it is not defective. However, 3D deviation graph applying until ICP (b) looks like that about 3mm defects occur at the end of product even if tested part is normal product. Therefore, if registration result is not accurate, it can lead to wrong result for defect identification.

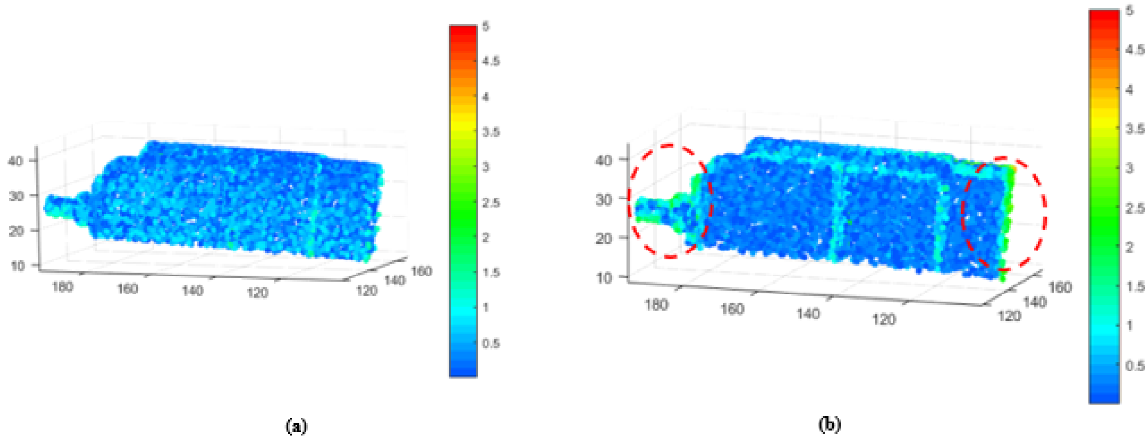


Figure IV-7. 3D deviation graph of (a) proposed registration method (b) ICP

The registration performance can be evaluated by recorded registration time. Measurement speed is important for in-process product measurement. 20 registrations were performed using ETH with difference angular shift. Mean recorded time was 12.468 seconds, Maximum recorded time was 14.502 seconds and minimum recorded time was 10.869 seconds. Therefore, 15 seconds is appropriate to cycle time of quality inspection of ETH.

4.2.2 Machining error detection

Experiment is conducted whether a defect in the incorrectly machined housing can be found. Defect on surface may affect the registration performance. Two types of defects were generated. One is a product that is longer than the original product. The other is a thicker part of the side with less cutting. Each product gave angular variations of 4.5, 9, and 18 degrees in roll, pitch, and yaw, respectively. Also, it was set to be 150 mm away from the design coordinate system in the x-axis direction and 60 mm away from the design coordinate system in the y-axis direction.

As a result, measurement coordinate system is aligned with design coordinate system with high accuracy. Figure IV-8 shows that the proposed registration work well even minimum error tolerance, 2mm. Deviation graph clearly shows the area of defect on the surface of object with red color. Therefore, it is appropriate for measurement application of randomly positioned objects.

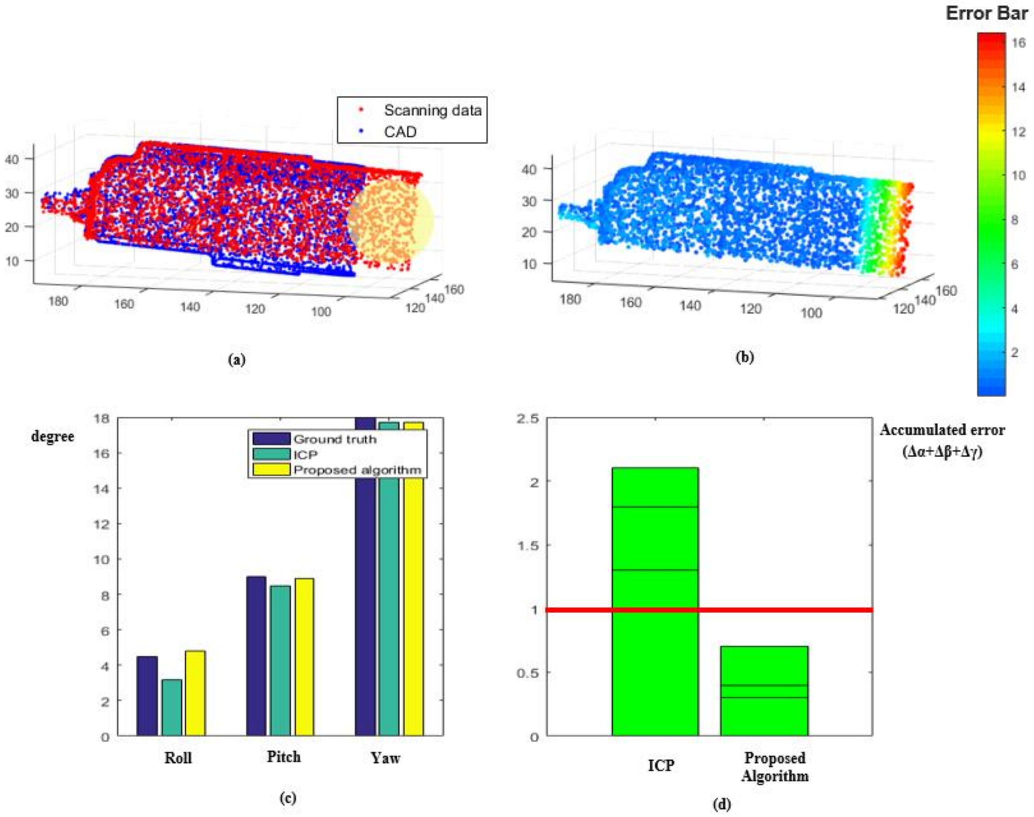


Figure IV-8. Result of faulty ETH (defect A)

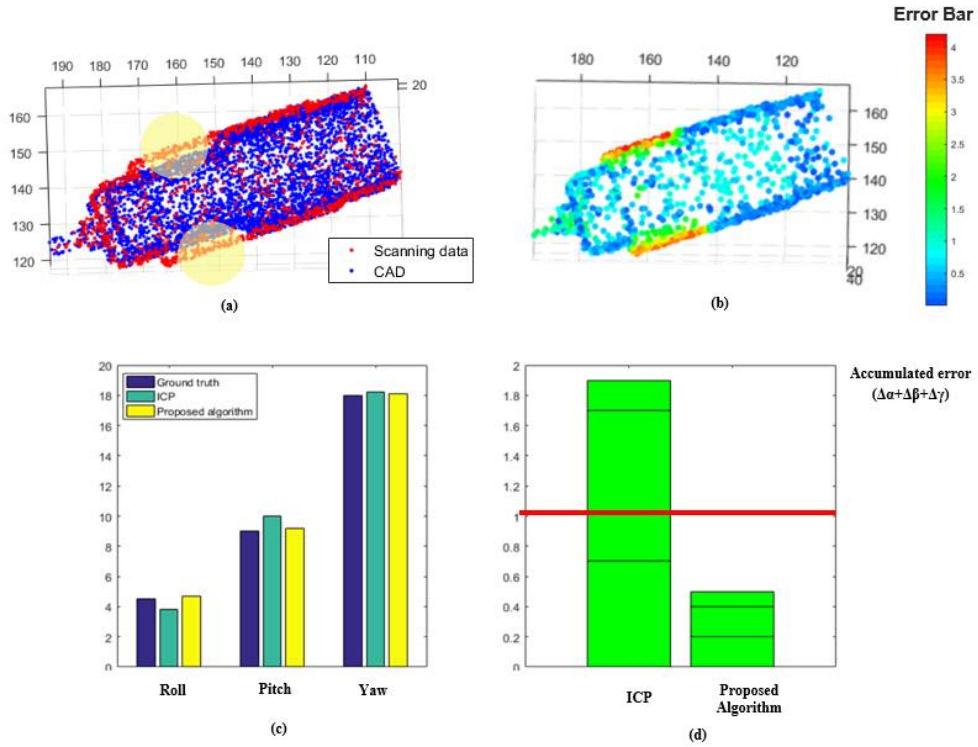


Figure IV-9. Result of faulty ETH (defect B)

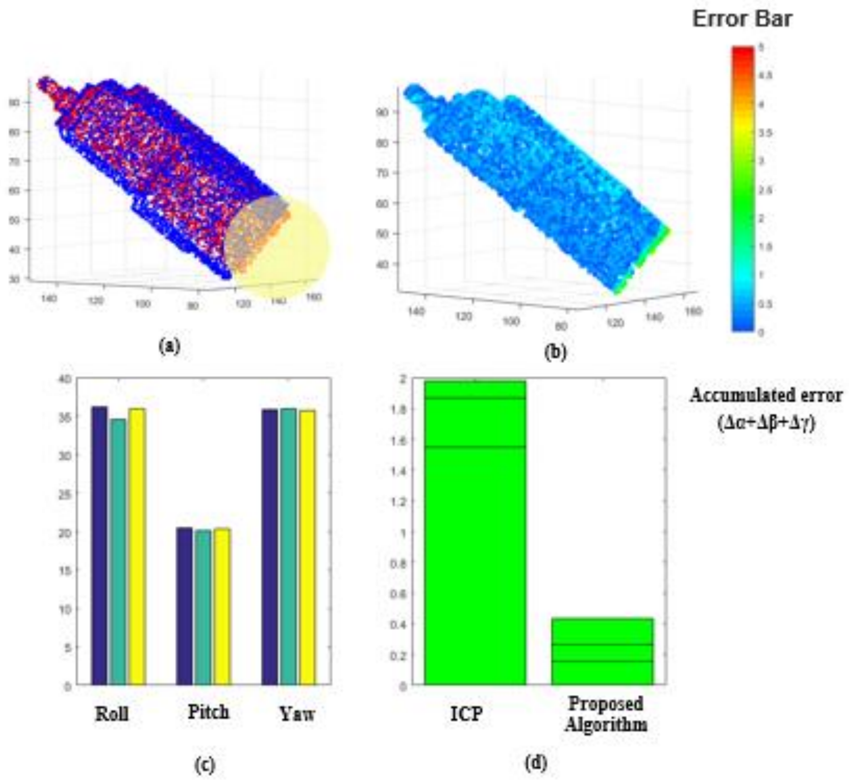


Figure IV-10. Result of faulty ETH (defect C)

V. Conclusion and Future Research

5.1 Conclusion

The measurement without physical calibration offers opportunities to reduce time and cost effectively in manufacturing industry. This measurement requires robust and effective means of registering these measured point cloud data and point cloud generated from CAD model. Therefore, a method of coordinate recognition was proposed for measurement of randomly positioned objects. Coordinate adjustment is added to conventional registration processes since fine registration of 3D datasets using Iterative closest point should be more robust for measurement application.

By considering those, a coordinate adjustment approach is proposed to calibration transformation parameters composed of rotation matrix and translation vectors. Reference plane matching algorithm based on reference plane selected by user is used to derive accurate rotation parameters. Also, the system will measure the object only once using 3D data acquisition device of non-contact types since this methodology pursues fully automated and real-time inspection application for in-process product. Reference plane selection is carried out considering constraints from these conditions. Therefore, this thesis suggest guideline for proper reference plane selection. After calculating of reliable Euler angle variation, translation parameters were calibrated by edge matching algorithm.

Experiment were conducted to compare the proposed system to conventional registration. All results show that it looks like registration of two datasets is aligned with high accuracy with only small variance. Accumulative error values of rotational parameters, roll, pitch, and yaw, are less than 1° in common. The result applied until conventional fine registration algorithm, iterative closest points, shows that the cumulative error is more than twice value of proposed algorithm. Experiment is conducted to test how robust the algorithm to defect. Defect on an object may be affect the registration performance since shape of object is transformed. However, the proposed method is worked with robust quality. Also, deviation graph clearly shows which area is defective.

We concluded that the proposed system suggested robust registration methodology with acceptable tolerance. Therefore, it seems suitable for used in 3D measurement system for in-process product. Also, it can work on bin picking system combined with object recognition and segmentation.

5.2 Future research

In this thesis, reference plane matching is performed after ICP. However, it can be developed as a future research that ICP is used as fine registration method after reference plane matching as a feature-based matching like conventional registration process.

At first, scanning data are segmented to each plane. Then, the most reliable plane, that is, the widest plane, is set as the reference plane. The size of the reference plane is used to find the corresponding to the reference plane on the CAD model. A plane similar size to the reference plane estimated from the scanning data is searched on the CAD model. At this time, several faces can be estimated as candidates on the CAD model. In order to narrow down the scope of reference plane in CAD model, we extract another plane near the reference plane on the scanning data. This becomes the second reference plane. Based on the size of the second reference plane and the angle between the first and second reference plane, the reference plane candidates on CAD model can be narrowed down. When considering the information of angular relationship between the first reference plane and the second reference plane, some tolerance should be given. After that, the third reference plane close to the two reference planes can be extracted in the same way for more reliable reference plane matching. It should be considered how much the angle of roll, pitch, and yaw of the entire body should be rotated when the angular relationship between the three reference planes may not exactly match the CAD model. Scanning data is rotated until the normal vector of the reference plane on the CAD model and the normal vector of the reference plane in scanning data to be the same. ICP is performed for fine registration after finishing reference plane matching. Edge matching step proposed in this thesis can be skipped since ICP provides transformation parameter for both rotation and translation.

In this thesis, we set the reference plane in advance and find the corresponding reference plane in the scanning data. However, the method proposed as a future work can be used with more dynamic angular changes of object because the reference plane can be determined flexibly regardless of the angle at which the object is measured. However, the area of the reference plane is key information for this method. Therefore, it is necessary to generate the mesh precisely so that the area can be calculated accurately when dividing the initial scanning data into faces

2D vision can be used to verify that the estimated pose is reliable. After projecting the data on the XY plane, we can confirm that the boundary of projected data and the envelop of object measured by 2D vision are the same. This process can be used for more sophisticated calibration. As another approach, it will be useful for coordinate registration if marker is added on the product at the design state of the product.

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